An integrated operation and maintenance framework for offshore renewable energy

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I certify that all material in this thesis which is not my own work has been identified and that no material has previously been submitted and approved for the award of a degree by this or any other University.

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Abstract

Offshore renewable devices hold a large potential as renewable energy sources, but their deployment costs are still too high compared to those of other technologies. Operation and maintenance, as well as management of the assets, are main contributors to the overall costs of the projects, and decision-support tools in this area are required to decrease the final cost of energy.

In this thesis a complete characterisation and optimisation framework for the operation, maintenance and assets management of an offshore renewable farm is presented. The methodology uses known approaches, based on Monte Carlo simulation for the characterisation of the key performance indicators of the offshore renewable farm, and genetic algorithms as a search heuristic for the proposal of improved strategies. These methods, coupled in an integrated framework, constitute a novel and valuable tool to support the decision-making process in this area.

The methods developed consider multiple aspects for the accurate description of the problem, including considerations on the reliability of the devices and limitations on the offshore operations dictated by the properties of the maintenance assets. Mechanisms and constraints that influence the maintenance procedures are considered and used to determine the optimal strategy. The models are flexible over a range of offshore renewable technologies, and adaptable to different offshore farm sizes and layouts, as well as maintenance assets and configurations of the devices.

The approaches presented demonstrate the potential for cost reduction in the operation and maintenance strategy selection, and highlight the importance of computational tools to improve the profitability of a project while ensuring that satisfactory levels of availability and reliability are preserved.

Three case studies to show the benefits of application of such methodologies, as well as the validity of their implementation, are provided.

Areas for further development are identified, and suggestions to improve the effectiveness of decision-making tools for the assets management of offshore renewable technologies are provided.

Acknowledgements

This work would not have been possible without the support of a number of people who shaped me as an independent researcher and better individual.

Firstly, I am very grateful to my team of supervisors at the University of Exeter, Professor Lars Johanning and Dr Philipp Thies, for giving me the opportunity to carry out this work and for their valuable support and guidance throughout my PhD. I would also like to thank Dr Ajit Pillai for proofreading this work and for the time and support he has generously provided. The technical advices of my colleagues and friends at the Renewable Energy cluster, as well as their help in making this experience so pleasant, are also gratefully acknowledged.

I would like to sincerely thank the financial support of my funders. The European Union, which funded this research and training activities for two years through the OceaNET programme, and Mojo Maritime Ltd., which provided the funding for a year and a half allowing me to enroll in a PhD. The strong expertise and practical guidance offered by the whole team at the company is also greatly appreciated.

Special thanks go to my family and friends for their infinite encouragement and approval, particularly to my parents and brothers. And my greatest thanks to my partner Jessica, for the emotional support provided and for sticking with me in my relocations across Europe.

Finally, any errors, omissions or oversights in this work are entirely my own.

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Nomenclature

Acronyms

CAPEX Capital Expenditures

cdf cumulative distribution function

CM Condition Monitoring

CTA Critical task analysis

CTV Crew Transfer Vessel

ECN Energy research Centre of the Netherlands

ETA Event tree analysis

FMECA Failure mode, effects, and criticality analysis

FTA Fault tree analysis

GA Genetic Algorithm

HAZOP Hazard and operability studies

HMM Hidden Markov Model

ITN Initial Training Network

MCDM Multi-Criteria Decision Making

MCMC Markov Chain Monte Carlo

MDP Markov Decision Process

NOMENCLATURE

MILP Mixed Integer Linear Programming

O&M Operation and Maintenance

OPEX Operational Expenditures

ORE Offshore Renewable Energy

OW Offshore Wind

OWC Oscillating Water Column

OWF Offshore Wind Farm

OWP Offshore Wind Project

PCA principal component analysis

pdf probability distribution function

POMDP Partially Observable Markov Decision Process

PRNG Pseudorandom Number Generator

QRA Quantified risk analysis

RBD Reliability Block Diagram

RBI Risk based inspections

RCA Root cause analysis

RCM Reliability Centred Maintenance

ROV Remotely Operated Vehicle

SCADA Supervisory Control And Data Acquisition

SMDP Semi-Markov Decision Process

SWIFT Structured What-if technique

TPM Total productive maintenance

TSD Tidal Stream Device

VEGA Vector Evaluated Genetic Algorithm

WEC Wave Energy Converters

List of publications

The following publications and contributions have been produced as a consequence of the work implemented during this thesis:

1. Rinaldi, G., Thies, P., Walker, R. & Johanning, L. (2016c). On the Analysis of a Wave Energy Farm with Focus on Maintenance Operations. *Journal of marine science and engineering*, **4**

2. Rinaldi, G., Thies, P., Johanning, L. & Walker, R. (2016a). A computational tool for the pro-active management of offshore farms. In *2nd International Conference on Offshore Renewable Energy*, 111–115, ASRANet Ltd, Glasgow, UK

3. Rinaldi, G., Thies, P., Johanning, L. & Walker, R. (2016b). A novel reliability-based simulation tool for offshore renewable technologies. In C. Guedes Soares, ed., *2nd International Conference on Renewable Energies Offshore*, 775–784, Lisbon, Portugal

4. Rinaldi, G., Thies, P. & Johanning, L. (2017a). A coupled Monte Carlo - Evolutionary Algorithm approach to optimise offshore renewables O & M. In *12th European Wave and Tidal Energy Conference*, 1–7, Cork, Ireland

5. Rinaldi, G., Thies, P., Walker, R. & Johanning, L. (2017b). A decision support model to optimise the operation and maintenance strategies of an offshore renewable energy farm. *Ocean Engineering*, **145**, 250–262

6. Rinaldi, G., Pillai, A., Thies, P. & Johanning, L. (2018b). Verification and benchmarking methodology for O&M planning and optimization tools in

the offshore renewable energy sector. In *37th International Conference on Ocean, Offshore and Arctic Engineering*, Madrid, Spain

7. Rinaldi, G., Portillo, J., Khalid, F., Henriques, J.C.C., Thies, P., Gato, L.M.C. & Johanning, L. (2018c). Multivariate analysis of the reliability, availability, and maintainability characterizations of a spar–buoy wave energy converter farm. *Journal of Ocean Engineering and Marine Energy*

8. Rinaldi, G., Pillai, A., Thies, P. & Johanning, L. (2018a). Multi-objective optimization of the operation and maintenance assets of an offshore wind farm using genetic algorithms. *Wind Engineering*, (under review).

The content of this thesis has been expanded on the basis of the above papers. In particular, the case studies presented (sections 4.1, 4.2, 4.3, and Appendix A) are based on papers 5, 6, 8 and 7 respectively.

Chapter 1

Introduction

Contents

1.1 Background and motivation

Over the last 50 years the global average temperature has increased at the fastest recorded rate, and there is now general agreement among scientists that climate change is a reality and anthropogenic activities are a major cause (Pachauri *et al.*, 2014). Furthermore, increases in both the world population and energy demand are expected in the coming years (BP p.l.c, 2018; U.S. Energy Information Administration, 2017). For these reasons, the quest for innovative and alternative forms of energy generation, which are able to simultaneously satisfy the increasing energy demand while also reducing the emissions and pollution levels, are of paramount importance.

Under appropriate conditions, renewable energy technologies satisfy both these requirements and are becoming progressively more important in the global energy mix. In fact, they have been identified as the fastest-growing energy source accounting for 40% of the increase in primary energy (BP p.l.c, 2018). Among these, offshore renewable technologies, exploiting the energy of waves, tides, water currents, offshore winds and temperature or salinity gradients, hold the potential to play an important role in the future electricity supply from renewable sources. As they also help to reduce reliance on imported fuels, increase security of supply and can stabilise electricity prices, the number of projects aiming to exploit offshore renewable sources for the production of electricity has rapidly increased in the last few years. These technologies will permit investments in new geographic and technological areas, and will create job opportunities. At the same time, however, new challenges will need to be met in order to make this young sector competitive with more traditional technologies.

Indeed, due to the high costs related to the deployment of the devices, the cost of energy associated to offshore renewables is still too high to be competitive with that of conventional fossil fuel power plants (with an exception for some recent offshore wind projects), and a full understanding of the long-term environmental, societal, and economic impacts of offshore renewables is still needed.

A principal area of improvement is the technologies themselves: producing enhanced devices, capable of harvesting more of the energy contained in the oceans and with a better chance of surviving in extreme conditions, is pivotal (Esteban & Leary, 2012). On the other hand, improvements in the reliability and availability of the devices, as well as advances in their operation and maintenance (O&M) are also required. Both these enhancements aim to increase the productivity and reduce the running costs of marine energy converters, which, in turn, will lead to an increase in their competitiveness in the electricity market (Uihlein & Magagna, 2016).

The main factors affecting the final cost of the energy are the capital and operational expenditures (CAPEX and OPEX respectively), with the latter typically accounting for approximately 25-30% of the total costs (Martin *et al.*, 2016; Nielsen & Sørensen, 2011; Poulsen *et al.*, 2017). While technological advances in materials and components, as well as in production and manufacturing processes, are likely to decrease the CAPEX, the creation of models and standardised protocols that provide support to the management of an offshore energy farm is needed to reduce the OPEX. Logistics will play a pivotal role in this cost reduction, being a major focus for innovation where further work is essential in order to reduce cost for the offshore energy sector (Poulsen & Hasager, 2016). Under these circumstances, improving O&M practices and taking design choices that facilitate operational requirements has been indicated as one of the most cost effective approaches for mitigating the financial risks of offshore infrastructures (Shafiee & Kolios, 2015).

Although a number of works exist in the literature focused on characterising, and as a consequence improving, the decision-making process that guides the management of the assets of the farm, the proposal of alternative strategies and decisions is still a subjective process left to the experience, interpretation and engineering judgement of a decision maker. Besides, the selection of the strategic maintenance assets is rarely achieved in a single-stage process, being more often a time-consuming procedure requiring repeated optimisation runs in order to explore different possibilities or refine satisfactory solutions. However, the development of effective models and algorithms, possibly converted into decision support tools, would be highly beneficial in order to solve these issues and as a consequence favour the whole offshore energy sector.

1.2 Research context

The research described in this thesis originally began as part of a wider research consortium funded under the PEOPLE Programme (Marie Curie Actions) of the European Union: the multinational Initial Training Network (ITN) OceaNET (OceaNET, 2013). This consortium was structured in a number of research projects (work packages), aiming at contributing to the development of offshore wind and wave energy technologies. More specifically, the projects considered: an environmental monitoring hardware and software package, underwater electrical connectors and remotely operated vehicles (ROVs), air turbine for oscillating water column (OWC) wave energy converters and an O&M support software package. Within Work Package 5, concerned with the improvement of the conceptual approach, design and O&M of offshore renewable farms in terms of costs and safety, the task 5.2 consisted of establishing cost effective and reliable offshore procedures for wind and wave offshore farms by applying experience from the existing offshore industry (including oil and gas) and creating innovative offshore operation methodologies.

The OceaNET consortium would provide the necessary training through specific courses, and the University of Exeter the essential research approach of an academic institution. Mojo Maritime Ltd. (now part of James Fisher Marine Services), a company specialised in project management, engineering and consultancy services for the marine renewable energy industry, would bring the desirable industrial perspective to the problem.

Figure 1.1: Illustration of the collaborative research project which originated the work presented in this thesis.

Hence, after initial consultation between the two institutions involved in the work package (University of Exeter and Mojo Maritime), the project promptly turned into the development of a modelling tool that would allow for the characterisation of the key performance indicators of an offshore energy farm, in order to support the strategic, long term, decision making process for the logistics and assets management of the farm. For this reason, it would be initially referred to as *characterisation model*, and built in such a way to be adaptable to different devices, extending the range of technologies considered in the OceaNET project in order to include also tidal stream energy converters. Such adaptability would not only satisfy the requirements of the programme, but also procure added value with respect to the existing industry specific tools. Furthermore, the implemented tool would interact with, and contribute to the development of, Mermaid (Marine Economic Risk Management Aid), a commercial project planning tool for the risk mitigations on offshore operations proprietary to Mojo Maritime Ltd. (Mermaid, 2015; Morandeau *et al.*, 2013) and already available for the operational, short term, characterisation of offshore activities (including installation and maintenance procedures). At the present stage, in this work, Mermaid is used exclusively in order to calculate the response and transit times of the maintenance vessels. This will be further explained in section 3.1.1.4.

1.3 Research questions

Given the context and motivations introduced in the previous sections, the overarching question for this thesis is:

How can operation and maintenance procedures for offshore renewable energy farms be improved in an automated and systematic way?

To address this overarching question several areas of work are developed. Specifically, this thesis seeks to answer the following questions:

- Is there an effective way of modelling the long term operational dynamics of an offshore energy farm, in order to accurately estimate its key performance indicators?
- Given the information of the offshore farm and its productivity estimations, can the best logistics and maintenance assets be established in an ingenious and reliable way not necessarily subject to the experience and judgement of a decision-maker and in an acceptable time?
- What would be the potential implications of such tools and methodologies on the offshore farm maintainability and profitability?

1.4 Aims and objectives

In order to address the research questions set out, building on proven methods and extending their use to specific application for the offshore renewables sector, the main aim of this work is to *provide an integrated framework for the strategic improvement of the O&M assets and logistics of an offshore energy farm, by implementing a tool for the estimation of the key performance parameters and a model for the methodical and automated proposal of ameliorating alternatives.* This will result in a comprehensive characterisation and optimisation methodology for the O&M procedures of offshore renewable farms, and shall ultimately contribute to reduce the costs and increase the economic viability of ocean renewable devices.

The problem of finding the optimal combination of maintenance assets and improvements on the device is assessed through two modelling tools:

- The first model focuses on the prediction and estimation of the key performance parameters of offshore renewable farms using a Markov Chain Monte Carlo methodology, which is a common approach in this area;
- The second model is focused on finding the optimal value of each decision variable in the problem of optimising O&M and logistics, exploiting a novel approach that applies evolutionary algorithms to this context.

In this way, the complimentary strengths of two proven methods are combined in an integrated decision-support framework. Therefore, key objectives for this work are:

- Conduct a review of current literature to establish the status of computational models for the improvement of the operational phase of an offshore renewable farm;
- Through the literature review, assess priority areas for development within the offshore energy sector with a focus on improved farm profitability;
- Establish a suitable characterisation framework able to account for planned and corrective maintenance regimes, reliability of the devices, MetOcean limitations and maintenance assets capabilities;

- Develop a computational tool for the estimation of the energy yield and other energetic and economic parameters of the offshore farm over its life cycle;
- Identify appropriate recommendations for the improvements of the reliability, availability, maintainability and profitability of the offshore farm and identify further areas for development;
- Establish a suitable optimisation framework, able to consider the outputs of the characterisation model in order to provide support in the decision-making process;
- Provide a series of case studies which demonstrate the applications and the implications of using the developed tools on an offshore energy farm; and
- Discuss the findings from the case studies in the wider context of cost effective and reliable assets management solutions for offshore energy devices.

1.5 Research approach and thesis structure

Figure 1.2 anticipates the structure of the characterisation and optimisation procedure according to the methodology implemented in this work. This flowchart illustrates the process that, starting with data gathering, exploits a coupled approach in order to guide the optimisation of the offshore farm assets and the selection of the optimal O&M strategy. This is based on evolutionary algorithms and evaluation functions derived from a Markov Chain Monte Carlo characterisation model.

These approaches are chosen after extensive bibliographic researches due to a series of requirements they satisfy. For both models, the criteria that led to these choices are the high prevalence in literature on the investigated topics, the suitability to the proposed problem, the computational efficiency, the accuracy of the results, the adaptability to a coupled framework, and the ease of control and implementation.

For the Markov Chain Monte Carlo, additional considerations are the effectiveness in capturing and interpreting the operational aspects of an ORE farm, the degree of insight and flexibility it provides in doing so, and the wide acceptability in the industry.

For the evolutionary algorithms, additional considerations are the effectiveness in finding optimised solutions, the lack of necessity of knowing the solution space in advance, the good compromise between exploration and exploitation of the search space.

A quantitative assessment of the KPIs is thus combined with a qualitative evaluation, intended as relative comparison, of alternative strategies.

These justifications are further stressed and clarified throughout the thesis.

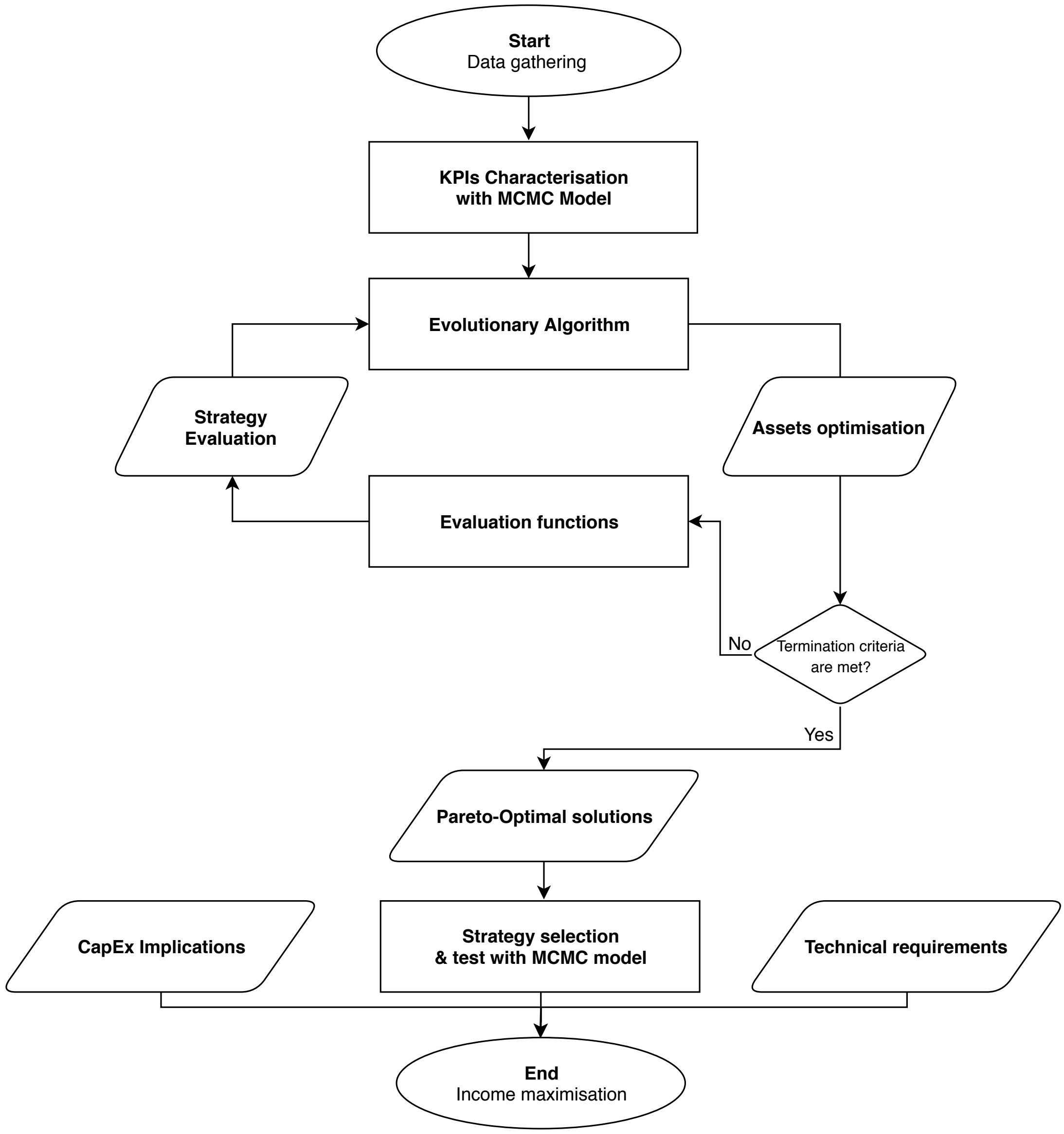

Figure 1.2: Flowchart of the implemented methodology.

Thus, the present work is structured as follows.

Chapter 2 defines the conceptual framework of this thesis, through a literature review of best practices and industry standards relating to operation and maintenance of offshore renewables. Existing modelling tools in this area are identified, and the nature of the approaches adopted in this thesis discussed.

Chapter 3 presents the characterisation and optimisation frameworks developed in this work individually, and outlines necessary inputs, generated outputs and eventual mechanisms and constraints.

Chapter 4 provides a series of three case studies looking respectively at:

- the characterisation of a tidal energy farm;
- the verification of the characterisation model and the benchmarking between this and the optimisation model; and
- the optimisation of an offshore wind farm.

This chapter is used to provide examples of applications of the methodology developed, showing the procedure to use the models and how to interpret the results obtained.

Chapter 5 discusses the outcomes, implications and limitations of the implemented methodology, both with reference to the case studies presented in Chapter 4 and in a generic context.

Finally, Chapter 6 summarises the content of this thesis and outlines a series of suggested improvements for future work.

A schematic representation of the content and structure of this thesis is provided in Figure 1.3.

Appendix A provides a further case study in order to show the applicability of the characterisation model on a wave energy converters farm and the use of multivariate analysis as an alternative to sensitivity analysis.

Appendix B provides a an example of the input sheets for the characterisation model.

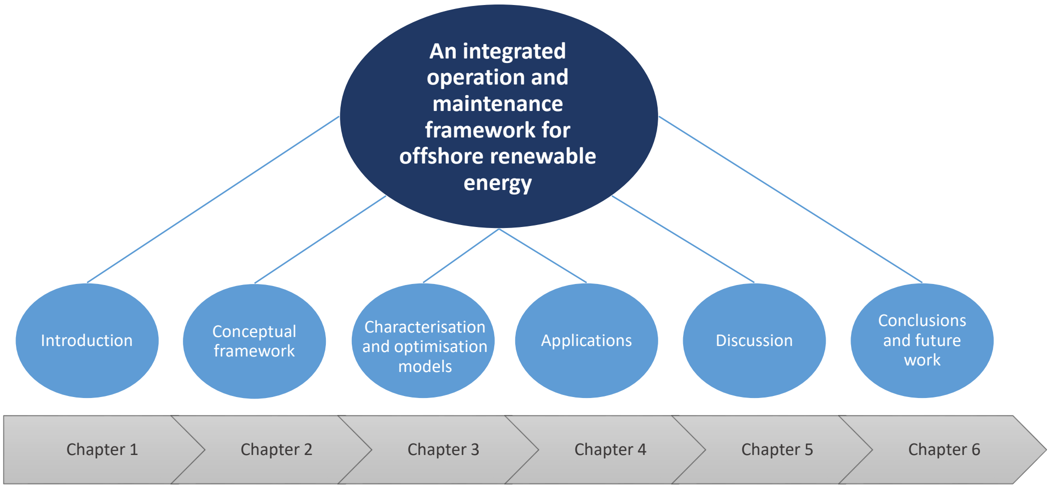

Figure 1.3: Thesis content structure.

1.6 Contribution to knowledge

The novel contribution provided by the present work consists in *laying the foundation for a complete characterisation and optimisation framework for the O&M and assets management of an offshore renewable farm.*

This is achieved through the implementation of a novel optimisation tool, exploiting genetic algorithms, in order to support the decision making process regarding the assets of the offshore farm rapidly, effectively and reducing the possibility of missing possible improvements measures if these are not proposed by the decision-maker. This constitutes the main novelty and contribution with respect to previous similar tools in this area.

Additional aspects described in this thesis, which were necessary to consider in order to achieve the main contribution above, are:

- An updated review of modelling tools in the area of operation and maintenance and logistics optimisation of offshore renewable farms;
- The development of a characterisation tool, flexible over different offshore technologies, in order to provide accurate estimations on the performance of the devices over their life cycle;

- The integration of reliability, weather, logistics and offshore operations in the above models and the overall framework; and
- The provision of a series of case studies representative of the O&M assets management problem in order to detail significance and implications of the implemented framework.

Chapter 2

Conceptual framework

Contents

Before presenting the developed characterisation and optimisation models in Chapter 3, this chapter outlines the main concepts needed to implement these models, and reviews the existing literature on these topics in order to identify the current state of knowledge and possible areas of development. First, Section 2.1 presents the basic definitions and main categories of operation and maintenance, focusing on strategies and applications for offshore renewable energy (ORE) technologies. Section 2.2 identifies existing computational models for the operation and maintenance of offshore renewables, while Section 2.3 introduces the Monte Carlo technique and its use for reliability modelling. Finally, Section 2.4 details the multi-objective optimisation framework with particular regard to the use of genetic algorithms in optimisation tools for offshore renewables.

2.1 Operation and maintenance

It is generally known that most items are subject to wear and degradation, processes which can lead to failure or breakage. For this reason, a series of activities aiming at keeping something in *operating conditions*, providing for its conservation and good use, and performing, if necessary, the appropriate repairs and replacements of pieces is commonly known as *maintenance.* According to the British standards (BS 3811:1993), operation and maintenance are defined separately as follows. Operation is defined as: "*the combination of all technical and administrative actions intended to enable an item to perform a required function, recognizing necessary adaptation to changes in external conditions*", whereas maintenance is defined as: "*the combination of all technical and administrative actions, including supervision actions, intended to retain an item in, or restore it to, a state in which it can perform a required function*". In other words, with specific reference to the industrial context, operation and maintenance (O&M) is that set of procedures which, following the installation and commissioning of a system, aim to keep it operational for its lifetime or a desired length of time under economic constraints.

An O&M strategy is commonly based on one or a combination of the following criteria: maximisation of reliability, minimisation of downtime and minimisation of total maintenance cost (Savic *et al.*, 1995). As a consequence, it involves both planned and unplanned activities that, in turn, generate both fixed and variable costs. The first type, fixed costs, generally involve administrative costs, insurances, rents or leases, planned maintenance activities and subcontract agreements, while the variable costs are limited to unplanned maintenance activities and spare parts cost. Additional actions can include overhauls or re-fits of still functioning components to improve their performance or extend the lifetime of the sub-systems to which these belong. Under these circumstances, the impact of O&M activities and the effort required to carry them out is extremely difficult to predict, and can vary significantly depending on the technology and a series of other, often unpredictable, variables. Nonetheless, it constitutes a significant amount of the overall cost of a project and for this reason investors demand accurate predictions for each of the contributors to the total operational expenditures (OPEX). OPEX are normally accounted in units of £/MW per year, or % of capital expenditures (CAPEX) per year, or £/MWh of electricity produced.

While several maintenance categorisations exist, two main O&M types are generally recognised: *corrective* and *preventive*. The principal difference between these two categories is that in a corrective strategy a problem is solved (e.g. a component repaired or replaced) only after the occurrence of the problem, whereas a preventive strategy tries to anticipate or avoid the problem before this arises. Within the preventive strategy, three sub-categories can be identified: *periodic*, *predictive* and *pro-active*. In a periodic strategy, maintenance is carried out at regular intervals (e.g. every 6 months, every 1000 cycles, etc.) regardless of the state of deterioration of the system as a precautionary measure. In a predictive strategy, additional instrumentation, often indicated as condition monitoring (CM) or supervisory control and data acquisition (SCADA) tools, is used in order to monitor the performance or status of deterioration of a component and, in this way, inform when maintenance is needed. Finally, a pro-active strategy is based on the use of preliminary information (e.g. reliability and failure data, as shall be discussed in section 2.1.2), as well as improvement loops developed as a result of experience with the same system, in order to estimate the right times for maintenance activities.

All the above categories are schematically represented in Figure 2.1, and graphically illustrated in terms of a generic component remaining lifetime (and consequent repair/replacement interval) in Figure 2.2 (here *failure* represents the corrective maintenance category). The main advantages and disadvantages of each maintenance strategy are summarised in Table 2.1.

Maintenance category	Advantages	Disadvantages
Corrective	- Cost effective for small components	- Possible costly downtime - Possible damage to associated equipment - High cost for medium/high priority equipment
Periodic	- Prevents system failures	- Often wasteful - Does not prevent certain failure - Can introduce problems - Requires large parts inventory
Predictive	- Reduces inventory cost - Reduces downtime - Reduces damage to associated equipment - Reduces unnecessary parts replacement	- When implemented alone, does not address root causes of problems - CM equipment are costly
Proactive	- Addresses root causes of problems - Reduces maintenance costs beyond predictive levels - Extends equipment life	- Cost

Table 2.1: Main advantages and disadvantages of different maintenance categories (adapted from Pillay & Wang (2003)).

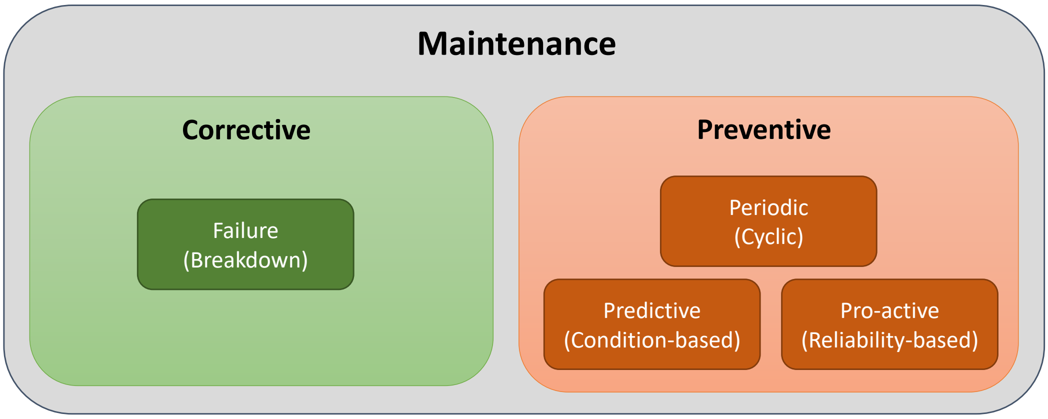

Figure 2.1: Categories of maintenance.

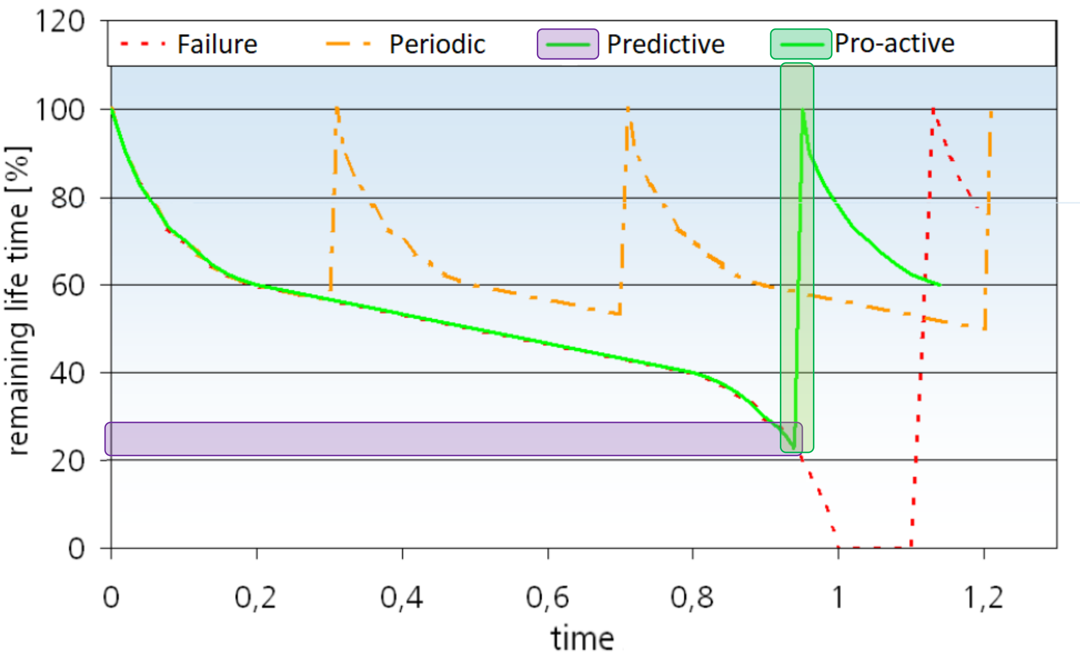

Figure 2.2: Repair/Replacement criteria depending on maintenance category. For the predictive strategy the remaining lifetime is measured by means of specific CM instruments, whereas in a pro-active approach this is estimated by taking advantage of preliminary information on the component. Adapted from P. Lyding (2011).

If the above categorisation relates to the timing of the maintenance actions with respect to the failures, another categorisation based on the effectiveness of the maintenance action, more specifically to the degree to which the operating conditions of a component are restored after maintenance, are provided by Pham & Wang (1996). In this categorisation five kinds of maintenance are identified, namely:

- **Perfect maintenance**. The system is restored to an *as good as new* state, resetting its failure distribution at the value for time t = 0 (as if it was a brand new component);

- **Minimal maintenance**. The system is restored to an *as bad as old* state, its failure distribution remains at the value it had before the failure (as if the component had not failed);

- **Imperfect maintenance**. The system is restored to an intermediate state between *as bad as old* and *as good as new*. An imperfect maintenance action can be interpreted as a generalised renewal process, and modelled by means of a virtual age model as illustrated in Equation 2.1 (Abdollahzadeh *et al.*, 2016). Here, the virtual age of a generic component after an imperfect maintenance action VA_{NEW} is calculated in function of the virtual age the component before that imperfect maintenance action VA_{OLD} and a parameter q. q is called *effectiveness* or *rejuvenation* parameter, related to the maintenance action efficiency, and falls within the intervall [0,1]:

$$VA_{NEW} = VA_{OLD} \cdot (1 - q) \tag{2.1}$$

- **Worse maintenance**. The system is restored to a functioning state but in worse conditions than before the failure, its failure rate or deterioration increases; and

- **Worst maintenance**. The system fails as an unintended consequence of the maintenance action (e.g. wrong adjustments or further damage during repair).

It has to be noted that perfect maintenance actions are generally more expensive and more difficult to achieve than minimal or imperfect maintenance interventions, and a combination of both is generally practised in industry (Do *et al.*, 2015).

2.1.1 Maintenance strategies and assets management for offshore renewables

As is the case in many industrial contexts, the area of marine renewables also requires a combination of both planned and unplanned activities in order to keep the devices operating in a safe and cost effective manner. Similarly, fixed administrative costs and ongoing condition monitoring of relevant components must be sustained. As an example, a breakdown of the typical O&M related costs for a wave energy converters (WECs) farm is illustrated in Figure 2.3 (The Carbon Trust, 2006).

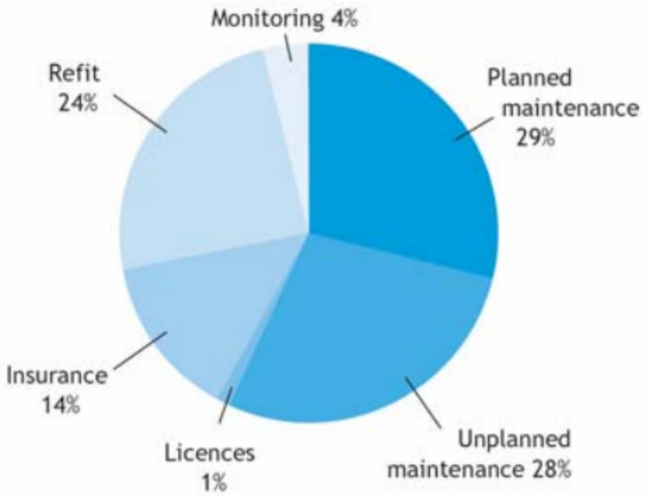

Figure 2.3: Breakdown of the O&M costs for an example wave energy farm (The Carbon Trust, 2006).

However, in the marine environment where the offshore renewable energy (ORE) devices are located, there is a series of additional issues compared to the planning of the O&M strategies for onshore systems. These include, but are not limited to (Pillay & Wang, 2003):

- higher degree of isolation from repair and spares facilities;
- higher cost of access systems;
- more severe safety and insurance conditions;
- varying costs and availability of the access systems (e.g. vessels and helicopters) due to fluctuations in the charter market; and

- varying costs and quality of labour and spare parts.

Though in some works the term “access system” refers to the actual means used to facilitate the transfer of technicians and provide them access to the devices (e.g. a gangway), in this work this term will indicate any generic vessel, workboat or helicopter used for the operation and maintenance activities. At the same time, the term “vessel” will be used as a synonym for a generic maintenance access system.

The amount (and cost) of maintenance procedures is strongly dependent on the ORE technology under consideration, the size and number of devices in the offshore farm and their distance from shore (and more specifically the distance from the maintenance port). In this regard, the use of a nearby warehouse or dry port might be beneficial in order to store spare parts and other assets.

Typical costs for the O&M of ORE farms include (The Carbon Trust, 2006):

- consumables and replacement parts;
- access systems charter/purchase and related servicing costs;
- spare parts storage;
- maintenance staff salary; and
- production losses due to downtime.

As a consequence, innovative logistical solutions are often required. In this case, the O&M activities aim not only at keeping the devices operational, but also and especially at achieving the ideal compromise between operating costs and energy production, as illustrated in Figure 2.4.

The criteria that should be used to select one maintenance strategy over the others are the maximisation of the availability of the farm, both in terms of time and, more importantly, energy produced, and the minimisation of the costs related to the running and management of the farm. At the same time, a compromise has to be reached between the improvement of the maintenance strategies and an increase of the O&M costs. In fact, a solution that maximizes the availability of the farm may not be the most cost effective if the maintenance efforts to reach that value, then the expenses related to these, are too high. In this way, an optimal balance between reliability

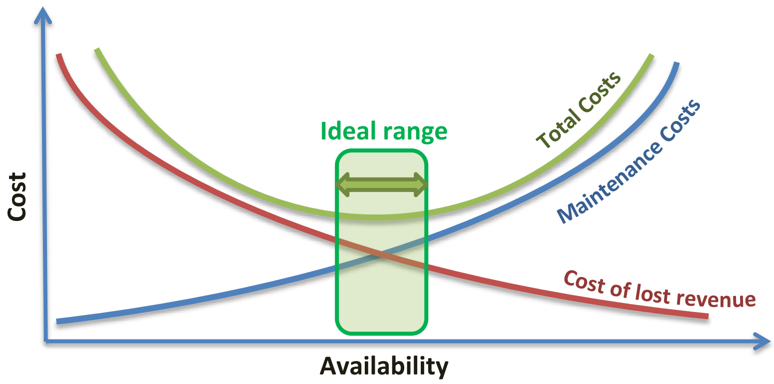

Figure 2.4: Balance between maintenance costs and energy production (adapted from DNV-GL (2013)).

(and/or availability) of the system and cost of maintenance tasks can be achieved. In this context, operation includes also high level management of the assets and electricity sales, while maintenance includes also surveys and inspections (DNV-GL, 2013). The objective is the achievement of the maximum electricity production at the minimum cost. Under these circumstances, maintenance interventions are ideally performed during low-resource period, in order to both minimise the energy loss and operate in favourable conditions for access systems and maintenance crews. For these reasons, an exhaustive and continuous monitoring of key environmental variables is usually required in order to assess the practicability of an intervention and establish if a suitable weather windows is available. This monitoring activity includes the observation of:

- winds (speed, direction, boundary layer profile, gusts);
- waves (significant height, energy or peak period, energy and directional spectral shape);
- tides (curents, speed, direction); and
- visibility (turbidity, fog, daylight).

However, in order to achieve the desired trade-off between energy production and maintenance costs, an effective management of both the onshore and offshore assets available and necessary for the efficient functioning of the devices, is required. This should provide useful information on the criticality of each asset, the risks to be avoided, the needs to be served, the details on the activities to be carried out with related measurability criteria and suggestions on possible improvements and dissemination activities (Lloyd, 2010). Among the series of tools and techniques which can be used to address these issues, the most popular are (Dinwoodie, 2014): Reliability centred maintenance (RCM); Total productive maintenance (TPM); Risk based inspections (RBI); Failure mode, effects, and criticality analysis (FMECA); Fault tree analysis (FTA); Event tree analysis (ETA); Critical task analysis (CTA); Hazard and operability studies (HAZOP); Quantified risk analysis (QRA); Root cause analysis (RCA); and Structured What-if technique (SWIFT).

One or a combination of these tools is usually used in order to test (and obtain useful indications for) the management and administration of the assets and logistics of the ORE farm, either onshore (e.g. port facilities, spares warehouse, maintenance crews), offshore (e.g. workboats, maintenance vessels, helicopters, substations), or device-related (e.g. number of inspections, CM instrumentation, redundancy elements).

Under these premises, in order to obtain the most cost-effective O&M solutions for an offshore farm a proactive approach is generally preferable. This should foresee possible issues and provide the guidelines to solve them, minimising the consequences of unintended disruptions. In fact, the strict accessibility limits of an offshore installation, which depends on weather conditions (waves, currents, visibility, etc.) and capabilities of the access systems (vessels, workboats, helicopters, etc.) must be taken into account. Therefore, a reactive strategy which postpones actions until a breakdown occurs should be avoided, though this may potentially be practical for ORE farms located close to shore in shallow waters (Shafiee, 2015). A cyclic (periodic) policy, that maintains the devices on regular intervals without further considerations or associations to other factors, should be avoided as well to minimise the risks of a too exhaustive, and therefore too expensive, maintenance plan. Other time-based interventions, based on past failure data to establish a replacement or inspection interval, may not be flexible enough in order to consider weather restrictions, vessels availability, unexpected failures and other generic unpredictable events. Similar considerations may apply to an approach exclusively based on condition monitoring, i.e. condition-based interventions. These strategies would monitor operational parameters such as pressure, temperature, vibrations and acoustic emissions, as well as the status and deterioration of components of subsystems allowing the operators to act accordingly based on these measurements. However, this strategy too is not without fault, as the installation of external instrumentation has an associated cost which increases the final costs of operation (although these are usually outweighed by the benefits of having a CM system (McMillan & Ault, 2007)). Furthermore, CM components can also be subject to failure, and even in the event that a problem is detected its resolution is still subject to the accessibility of the farm. In addition, the vast amounts of data that condition monitoring systems can generate raise further issues related with data compression, communication and standardisation.

For the reasons above, a combination of all these approaches taking advantage of the complementary advantages to the benefit of the farm, including additional considerations based on the reliability related information of the devices, should be preferred. In this way, the assessment of the optimal schedule for maintenance interventions, exploiting the reliability data available and prior to eventual breakdowns and related unintended disruptions, can be achieved.

Finally, when dealing with the organisation of the maintenance logistics for ORE farms, three main echelons of decision-making, also adopted in this work, can be distinguished: strategic, tactical and operational (Shafiee, 2015). Despite these echelons have been originally defined for offshore wind farms, they can be extended to generic offshore renewable farms. The first, strategic, represent those decisions that have long-term effects, typically more than five years to the whole life cycle of the offshore farm. Examples of strategic decisions include the placement of the devices, the size and location of the spare parts warehouse and other maintenance accommodations, and the maintenance strategy itself. The second type of decision-making, tactical, are those decisions that have medium-term effects, in the scale of several months up to five years, and have to be taken with the same intervals. Examples of these include whether to lease or purchase a maintenance vessel and the inventory of the spare parts. The last category of decision-making, operational, are those decisions that have to be taken on a daily basis in order to manage the offshore farm, with consequent short-term effects. Examples of these are the scheduling of maintenance tasks and the routing of the maintenance vessels. Due to their long-lasting effects, strategic and tactical decision, on which the present work focuses, have usually a greater impact on the profitability of the project.

2.1.2 Reliability data for offshore renewables

ISO 8402 (1986), defines reliability as "*the ability of an item to perform a required function, under given environmental and operational conditions and for a stated period of time*". Therefore, for an ORE technology, reliability may be defined as the probability that the device will perform its active function (i.e. generate electricity) for a specific period of time (e.g. the project lifetime). Among the reliability data of a device, the most relevant for the proactive planning of the O&M procedure are the failure rates of the individual components. Throughout this work, the term component will be used to denote any element of the device's infrastructure, e.g. subassembly, subsystem or individual item.

A failure is the inability of a system/subsystem to operate under the defined conditions (Spinato *et al.*, 2009) which may be quantified by statistical metrics like an associated probability distribution. In other words, the failure rates describe the failure behaviour of each component over its lifetime (Thies, 2012). Thus, reliability information are of fundamental importance not only at the early design stages, but also during the planning and operation of marine renewable energy systems, helping to reduce the significant costs associated to the deployment of these systems (Y. Li, 2015). The primary sources to obtain reliability information for ORE devices are:

- existing databases, provided by the individual suppliers, filled with data obtained in previous experiences with the same components;

- specifically adapted databases, extracted from existing information regarding the same components, but used in different environments, and properly adjusted with correction factors (Thies *et al.*, 2009) in a procedure called *Reliability Assessment*; and

- the accelerated or destructive testing of specific components (e.g. moorings or hydraulic rams) (Gordelier *et al.*, 2015; Rühlicke & Haag, 2013) in a procedure called *Component Reliability Testing*.

Presently, much of the data available in wind farm databases suffers from inaccuracy, inconsistency and incompleteness (Shafiee, 2015) and this concept is valid, even to a wider extent, also for other marine technologies. Hence, a combination of the methods above is the most effective choice in order to obtain reliability data for all the components of the device and adapt longstanding databases to a specific context. This is particularly important in the case of marine energy devices, which are generally characterised by limited experience. Furthermore, wave and tidal devices have not entered serial production yet, thus their component failure rates are only representative of prototypes.

Reliability assessment is an established stochastic tool widely-used for prediction of product performance with focus on optimisation of device availability. Ideally, the reliability assessment for ORE is based on statistical estimates of subassembly failure rates based on a large sample of failure events of identical devices deployed at locations with similar operational conditions. However, due to the broad range of equipment and operating conditions for ORE devices, compilation of such a detailed database is challenging.

Currently, due to the embryonic stage of the ORE industry, no industry-specific failure data is publically available, therefore, reliability data from more mature industries using similar subassemblies are commonly used to populate reliability models (Ambühl *et al.*, 2015; Mcauliffe *et al.*, 2015; Thies, 2012; Wolfram, 2006). Several extensive failure databases have been compiled in other industries like aviation, offshore oil and gas and electronics. So far, the Offshore Reliability Data (OREDA, 2009) handbook and its derivatives have primarily been the reference of choice since data for the handbook is collected from a marine environment. Also, the OREDA project provides high quality reliability data collated over extended period of time, covering a broad spectrum of structural and mechanical equipment. This, together with the US Military Handbook Reliability Prediction of Electronic Equipment (MIL-HDBK-217F, 1995), appears to be the most frequently used databases for reliability prediction and assessment (Thies, 2012) in the absence of more specific data sources. Examples of reliability database for ORE technologies populated by means of reliability prediction models can be found in Richardson (2010) (for offshore wind turbines), Delorm (2014) (for tidal energy devices) and Thies (2012) (for wave energy converters).

Nevertheless, failure rates extracted from databases are subject to interpretation by the analyst, and consequently must be adjusted for any change in the equipment use, operating environment, failure modes and applicability of data source (Thies, 2012). In order to avoid this issue and reduce the uncertainty for the offshore wind sector, in 2013 the collaborative project SPARTA (System performance, Availability and Reliability Trend Analysis) was initiated (ORE Catapult, 2015). This aims at the creation of a database for sharing offshore wind farm performance and maintenance information by exploiting the benchmarked and anonymised data provided by the participating offshore wind farms owners and operators. Unfortunately, the database is accessible only to the partners participating at the project and providing data. A project with analogous aims (produce a reliability database), led by the Fraunhofer Institute for Wind Energy and Energy System Technology (IWES), had been developed in Germany in 2011 (Fraunhofer Institute, 2011).

By taking advantage of these information, the right schedule for proactive maintenance measures is estimated on the basis of previous know-hows and without additional costs.

2.2 Computational models for O&M of offshore renewables

As mentioned in the introduction, in recent years a large number of computational tools have been developed to simulate different aspects of an ORE farm as well as improve the O&M planning and assets management. These tools aim to provide support in the decision-making process for one or a series of specific problems for which there is a degree of uncertainty about the optimal solution. Most of these models permit the analysis of different aspects of the functioning of the ORE farm, allowing the selection of the best combination of parameters in order to maximise the income of the electricity sale and minimise the overall expenses. Furthermore, these models try to overcome the lack of operational experience in the offshore renewable sector, and obtain robust estimates on the effectiveness of the farm. Due to the greater maturity of the offshore wind (OW) industry with respect to other marine renewables, specific O&M tools for offshore renewables have so far been focused mainly on this sector. Being in a more advanced stage of development, the faster spread and growth of this technology has augmented the needs for methodical ways of managing the assets of the OW farm, providing at the same time greater possibilities of application to developers who wanted to test and calibrate their models.

This section provides an overview of existing tools for the O&M planning of offshore renewable devices. Hence, diverse set of models, for different aims and planning horizons, not necessarily analogous to those of the tools implemented in this work, are presented. Nonetheless, since practical elements for the reduction of the modelling uncertainties and the refinement of the tools can be found also in these models, these are kept in the review.

Hofmann (2011) presented a comprehensive review of these models, identifying a total of 49 commercial and non-commercial decision support models specific for offshore wind farms. Reports, scientific databases, conference proceedings, research institutions, research projects, consultancies and wind organizations were investigated, and the models arranged in seven categories depending on their main purpose, i.e. the main aspect or cost driver to characterise. These included computational tools focused on the characterisation of: total project costs, operation and maintenance, failures and reliability, micro-siting and layout, components costs, installation and access, management tools. However, limited information is provided in terms of working principles of the models. More recently, Anaya-Lara *et al.* (2017) completed this review by providing an overview of the strategic O&M tools not included in the review by Hofmann (2011).

Nielsen & Sørensen (2014) provided an overview of various approaches for the risk-based planning of the O&M of wind turbines, comparing different solution methods, highlighting the accuracy and flexibility of Markov Chain Monte Carlo (MCMC) simulations, and concluding that these are the most accurate method of optimising the decision policy. Dawid *et al.* (2015) presented a review of academic works exploiting Markov models for maintenance optimisation in the context of offshore wind farms, discussing their suitability for successful application, and identifying the theoretical and practical gaps to increase their acceptance in the offshore wind industry. Here, Markov models are divided into Markov chains, Markov Decision Processes (MDPs), Hidden Markov Models (HMMs) and Partially Observable Markov Decision Processes (POMDPs), and the main features of these approaches in the context of maintenance optimisation described.

Endrerud *et al.* (2014) focused mainly on marine logistics aspects, developing a simulation model based on a generic simulation software (*AnyLogic*). This exploits a combination of agent-based and discrete event modelling techniques to simulate the O&M of offshore wind parks and obtain support in the decisions regarding: vessel fleet configuration, supply base location, wind turbine technology, staffing and work processes. Martin *et al.* (2016) implemented a model based on probabilistic failure events, which is used to repeat simulations of specific offshore wind projects varying one of the parameters at a time. In this way the importance of a sensitivity analysis in identifying the factors affecting operational costs and availability of an offshore wind farm is emphasised. Dawid *et al.* (2016) developed a tool, based on a Semi-Markov Decision Process (SMDP) approach, to support the short to medium term maintenance decision problem. Weather forecasts, time-varying failure rates and variable costs of vessel hire are considered in this work, and argumentations to opt for condition-based over time-based maintenance strategies presented.

However, to a lesser extent, also O&M tools for other marine renewable devices have been developed. Teillant *et al.* (2012) presented an example of techno-economical assessment, putting together a productivity and costs assessment module, which includes considerations on availability and operational costs of the power plant, with a financial calculator which employs discounted cash-flow techniques to estimate the economic indicators of a wave energy farm. Gray *et al.* (2017) developed an O&M simulation tool based on Monte Carlo simulation, and used it to assess the effects of variations of the components' failure rates on the profitability of a wave energy farm. In this case the failure rates were estimated using the expert judgement of the engineers involved in the development of the Pelamis P2 device, providing another example of reliability assessment combined with O&M planning. In 2013, the European Union funded DTOcean (DTOcean, 2013), a 3-years collaborative project which gathered 18 academic and industrial institution across Europe to produce an open-source suite of tools to support the design of wave and tidal energy arrays. Among other modules, a lifecycle logistics work package which takes into account the O&M strategy of the ORE farm is included, and can be used to obtain useful indications for the O&M planning, provided that adequate inputs to the tool are given (Fraunhofer IWES, 2014; Gray *et al.*, 2017).

Other models have been proposed to solve specific targeted problems or address only one of the aspects needed to define the final O&M strategy. Among these, Ambühl *et al.* (2016) implemented a combination of cost and damage models to assess the impact of weather forecasts and related uncertainty on power estimation and maintenance planning of a specific WEC. Mcauliffe *et al.* (2015) exploited a probabilistic economic model, adapted using a Monte Carlo software suite (originally developed as an engineering optimisation tool for liquefied natural gas supply chains and then adapted to the ORE sector) to assess the viability of a wave/offshore wind combined platform. Dalgic *et al.* (2013) used time-domain Monte Carlo O&M modelling to mainly focus on the properties of the maintenance fleet for offshore wind turbines. A preliminary estimation of the charter rate for jack-up vessels under different operational strategies, as well as indications on the most effective charter periods, is provided in Dalgic *et al.* (2013). Consequently, the identification of the optimum chartering strategy for jack-up vessels for three potential offshore wind farms in the United Kingdom is investigated in Dalgic *et al.* (2015c), while the size and capabilities of the optimal crew transfer vessel (CTV) fleet are investigated in Dalgic *et al.* (2015b) and the operational and financial benefits of multiple working shifts in Dalgic *et al.* (2015a). Similarly, the optimal fleet size and composition in order to support maintenance activities in an offshore wind farm located in the North Sea is investigated by means of a stochastic programming model in Stålhane *et al.* (2016).

While the majority of these models are concerned with reducing the effects of unplanned corrective interventions, a number of works aim at characterising and taking advantage of preventive planned interventions. The integration of preventive opportunistic maintenance actions while a failed component is replaced, and an estimation of this combined strategy on total O&M costs, is evaluated in Sarker & Faiz (2016). The use of historical in-service failure data for preventive maintenance task selection, and to determine the optimal planned maintenance interval required to maintain desired reliability of a typical component or sub-assembly of wind turbines with special focus on the gearbox, is investigated in Igba *et al.* (2015). A combination of stochastic Petri Nets and Monte Carlo simulation is used to measure the effectiveness of age-based preventive repairs on corrective replacements of offshore wind turbines, in Santos *et al.* (2015).

Finally, though the majority of the literature is available for academic models, a limited number of commercial software exist. One of the first examples was the ECN O&M Tool (Curvers A.P.W.M., 2004a,b; Ramakers R. & L.W.M.M., 2004) by the Energy research Centre of the Netherlands (ECN), a validated software developed in Excel which uses a probabilistic assessment methodology in order to estimate the operational costs of offshore wind farms and provide a database for failure rates and maintenance logs. The same institution further improved this tool by including considerations on the condition-based maintenance activities, in order to extend its usability to the operational phase of the offshore wind farm rather than the preliminary planning phase only. This led to the creation of the Operation and Maintenance Cost Estimator (OMCE) (Braam *et al.*, 2011), released to market in 2011. Another example is the software MAINTSYS (MAINTSYS, 2015), initially developed as a part of a PhD project at University of Stavanger and the Norwegian Centre of Offshore Wind Energy (NORCOWE) and which includes a library based on publicly available data containing vessels, helicopters, ports and wind farm assets.

Furthermore, one of the findings in Hofmann (2011) was that large consultancies and utilities often have tools to simulate aspects of offshore wind farms; most of these are usually not available outside the company. Examples are the Monte Carlo ECUME model developed by EDF R&D (Douard & Lair, 2012) to support the groups activities in the offshore wind industry, and the Norwegian offshore wind power life cycle cost and benefit (NOWIcob) (Hofmann & Sperstad, 2013) developed by SINTEF Energy Research.

2.3 Markov Chains and Monte Carlo stochastic modelling

When a complex system like an ORE farm has to be modelled, a deterministic approach is impractical due to the nature of the involved variables and the difficulty in understanding the interdependencies among its elements. For this reason, an approach that takes into account both the stochastic variability (randomness) of the key parameters and the intricate dynamics of the project is required. As a consequence, stochastic simulation is generally applied in order to quantify the evolution of one or a set of variables whose value can change randomly and according to a certain probability distribution (Alexander, 2003). A number of probabilistic evaluation techniques exist to model the reliability of the system and provide an assessment of the maintenance procedures. However, if the modelling of random events (e.g. unexpected failures) is the objective, Markov models and Monte Carlo simulation are the most widely used approaches (Hofmann, 2011) due to their degree of flexibility and level of understanding provided.

Markov models are random processes used to represent a generic chain of events characterising the state of a system (Bhat & Miller, 2002; Norris, 1998). The distinguishing property is that these transitions are memory-less, i.e. under the assumption that a transition from a state to another depends exclusively on the current state, and not to what happened previously (previous event or transition). A transition probability is used to express the likelihood of passing from a state to another, and, provided that a starting probability vector is assigned, a transition probability matrix can be used to make a prediction about the state of the system at the generic time t. The sum of all probabilities of transition towards the possible states equals 1. In reliability engineering, Markov chains can be used to characterise the physical state of a system, e.g. an offshore renewable device, and the probability of transition between two states, e.g. working or not working.

On the other hand, Monte Carlo techniques are a set of non-deterministic estimation procedures which rely on repeating a sampling of determined quantities for a sufficient number of times in order to obtain an approximation of a quantity of interest (Kastner, 2010). In this way, the variability of the inputs is exploited in order to overcome the uncertainties about their exact value. Each individual repetition results in an independent estimation of what occurred in the simulated system. Hence, a series of different outcomes is obtained, from which the most likely estimate can be identified by averaging over all the results. As the number of simulations increases, the sample mean of these independent estimates approaches the actual characteristics of the system (Verma D., 1989). In addition, ranges of variations and associated probabilities are estimated for each scenario. In reliability engineering, Monte Carlo analysis uses reliability data and statistical distributions to define the most likely behaviour of the system over the considered period of time.

Markov models and Monte Carlo simulation can be easily integrated in an individual class of approaches that sample from a probability distribution, called *Markov Chain Monte Carlo* (MCMC) (Berg & Billoire, 2007; Geyer, 1992). In this way, random numbers are used to determine the state of the system in a discrete-time simulation, while repeated sampling gives to the problem the statistical approach required.

2.3.1 Monte Carlo method and reliability modelling

The occurrence of a failure is a probabilistic event whose likelihood depends on many factors, either due to the intrinsic nature of the considered system (or single component) and/or due to external circumstances. The first factor somehow reflects the quality of the materials, technical properties, engineering skills and manufacturing processes adopted to obtain the item; the second represents the effects of environmental factors, loads and usage conditions. In order to allow for the intrinsic aspects of a component its failure rate has to be considered, taken as the frequency of failures over a given period. As discussed in Section 2.1.2, this value has to be established with data obtained in previous experiences with the same component (Carroll *et al.*, 2016) or, when this is not available, adapted from existing databases (e.g. OREDA (2009)) or surrogate data using engineering judgement. Other circumstances, such as weather conditions and the marine environment, as well as the age of the component, can lead to a decrease or increase of the failure rate. Consequently, power rating and environmental stress factors can be considered in order to adjust failure rate values.

Therefore, depending on the factors influencing the variability of the failure rate considered, and the probabilistic distribution chosen (or available) to represent its failure behaviour, the failure rate assumes a value which can be either constant or variable over time. A classic example to show these effects is the well-known bathtub curve shown in Figure 2.5 (Klutke *et al.*, 2003), which gives a basic illustration of the variation of failure rate $\lambda(t)$ over time for a generic component. Here, the first part represents a decreasing failure rate typical of early fabrication and installation errors, the second part a constant failure rate typical of random unexpected failures during the useful life of the component and the last part an increasing failure rate due to ageing and degradation.

Other effects, for instance serial defects, can be incorporated as more pronounced variations if needed. An example is provided by Stiesdal & Hauge-Madsen (2005), in which the effects of serial failures due to premature wear-out of the components, result of rapid product development, are considered.

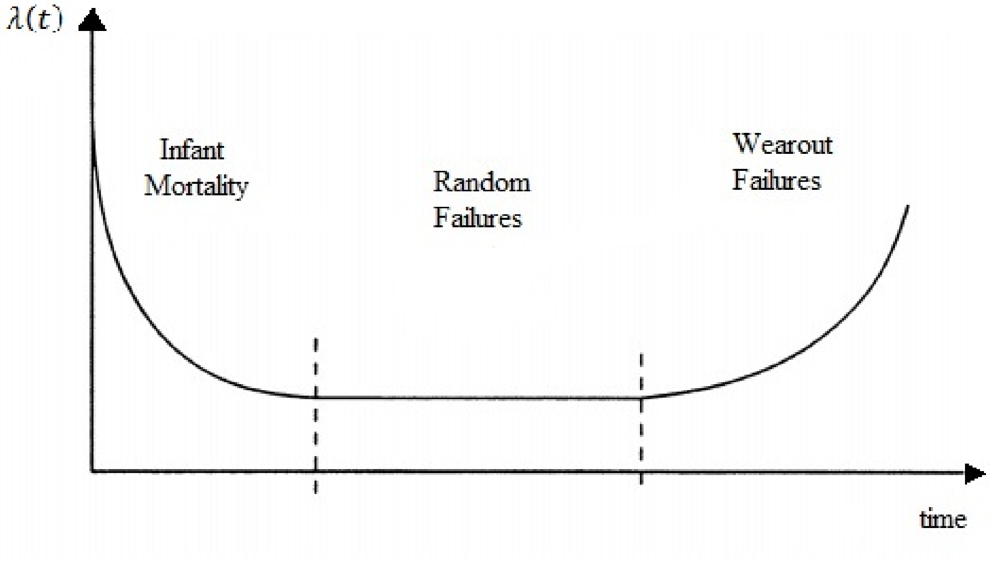

Figure 2.5: Bathtub curve, representing the variation of the failure rate of a generic component with time.

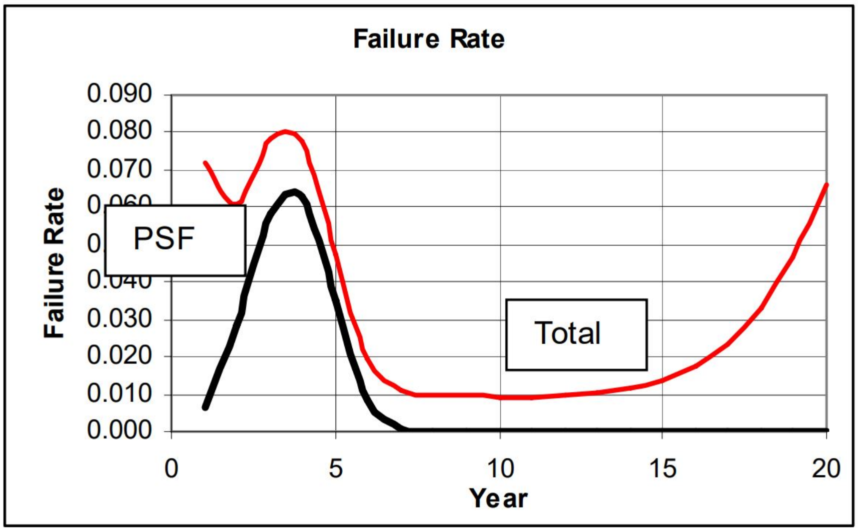

Figure 2.6: Bathtub curve including premature serial failures. The premature failures phase is shown in black, whereas the resulting bathtub curve in red.

In repairable systems, the failure rate describes at what rate (in failures/hour) the failures occur within a particular time interval [t_1, t_2] if no failure has occurred up to

t_1 (Thies, 2012), and its value is given by the expression:

$$\lambda(t) = \frac{f(t)}{R(t)} = \frac{f(t)}{(1 - F(t))} \tag{2.2}$$

where $f(t)$ is the probability distribution function (pdf) of the failures and $F(t)$ is the cumulative distribution function (cdf) of the failures. $R(t)$ is the reliability function of the component and expresses the probability that the item will remain in its operational state (i.e. has not failed) at time t:

$$R(t) = \int_t^\infty f(\tau)d\tau = 1 - F(t) \tag{2.3}$$

The suitability of a statistical distribution in adequately representing the failure rate of a component can be evaluated by a goodness of fit test procedure (Scheu *et al.*, 2017). Despite the various statistical distributions available to represent the stochastic failure behaviour of a generic component (Leemis, 1995), the most commonly used, and widely applicable due to their simplicity, are the exponential for a constant failure rate or Weibull for a variable one (Center for Chemical Process Safety, 2010).

Exponential failure distribution:

$$R(t) = e^{-\lambda t} \tag{2.4}$$

Weibull (2 parameters) failure distributions:

$$R(t) = e^{-\frac{t}{A}^B} \tag{2.5}$$

where A and B are the scale and shape parameters, respectively. Hence, depending on what failure distribution is chosen, different parameters have to be specified in order to take into account the reliability of a component and the entire system. Scheu *et al.* (2017) investigated the use of different failure distributions to understand the implications of statistical uncertainty for offshore wind turbines reliability estimates. They concluded that the choice of the failure distribution has a significant impact on the predictions on the performance of the assets, and, despite it being the most common approach, the use of constant failure rates may lead to inaccurate results.

A value often used as alternative to the reliability function is the Mean Time To Failure (MTTF), which denotes the mean functioning time of the item and represents its life expectancy value. Using the exponential failure distribution, its value for each component is given by the inverse of the failure rate:

$$MTTF = \int_0^\infty R(t)dt = \int_0^\infty e^{-\lambda t} = \frac{1}{\lambda} \tag{2.6}$$

Under these circumstances, a statistical time-domain approach, based on the Monte Carlo simulation technique can be used to represent the stochastic nature of failures. The characteristics of the Monte Carlo method make it ideal for reliability predictions when the complexity of the system prevents the formulation of exact models (Korver, 1994). The reliability of a generic component is modelled by means of a probability distribution. Thus, the Monte Carlo method repeatedly compares suitably generated pseudorandom numbers[1] against a set of predefined variables (i.e. the failure rate for each timestep and each component of the simulated lifecycle). This process is repeated for a sufficient number of times in order to cover all the possibilities and provide unbiased results. In this way, the most probable scenario is identified among a series of different possible outcomes. This allows the understanding of the impact of risk and uncertainty in each simulation, establishing probabilities of exceedance and confidence intervals on the results obtained.

This methodology, exploiting proper reliability data, can be used to perform the energetic and economic characterisation of ORE farms by simulating the failures that limit the functioning of the devices, and consequently, their availability and productivity. A failure is simulated when the following condition is satisfied:

$$N_R \geq e^{(-\lambda(t))^B} \tag{2.7}$$

[1]In order to achieve this, a pseudorandom number generator (PRNG) is used to generate numbers uniformly distributed in the range [0, 1]. A PNRG generates values that seem to be completely random (i.e. can satisfy common tests for statistical randomness), but in reality are generated exploiting a deterministic algorithm, with the key advantage that the exact same sequence of random values can be re-obtained in successive simulations by starting from the same "seed" state in the generator (L'ecuyer, 2010). This is a key property in order to guarantee repeatability of the simulation. The PRNG used in this work exploits the MATLAB built-in Mersenne Twister algorithm, which generates primes of the form $2^p - 1$ where p itself is prime.

where N_R is the pseudorandom number generated, λ is the failure rate of the considered component of the system and B is the shape parameter of the distribution. $B = 1$ in the case of the exponential distribution. A logical 0 is then assigned to the status of the component if a failure has happened, while a logical 1 is assigned otherwise. This method, combined with the Monte Carlo simulation, has been broadly adopted in Reliability analysis (Alexander, 2003; Bø, 2014; Takeshi, 2013).

In addition, in order to predict the reliability of a device, the reliabilities of the individual components that constitute it, and their configuration, must be considered. Depending on the mutual links and dependencies among components, these are typically interpreted as arranged either in series or in parallel. In a series configuration the failure of any of the components results in the failure of the entire system or sub-system, whereas in a parallel configuration at least one of the units must function for the system or sub-system to remain operational. Therefore, if x_i is the status of the generic component (Korver, 1994):

$$x_i = \begin{cases} 1 & \text{if component } i \text{ is in a good state} \\ 0 & \text{if component } i \text{ has failed} \end{cases} \tag{2.8}$$

and if Y is the status of the complete system:

$$Y = \prod_{i=1}^{n} x_i \tag{2.9}$$

for components in series, and

$$Y = 1 - \prod_{i=1}^{n} (1 - x_i) \tag{2.10}$$

for components in parallel.

This difference is illustrated in Figure 2.7 by means of reliability block diagrams (RBD), a combinatorial model that was initially proposed for determining the overall system reliability through intuitive block diagrams (Ebeling, 2004). This can be used to graphically represent the components of the system and their mutual dependencies. Depending on the context, components in parallel are indicated as redundant elements.

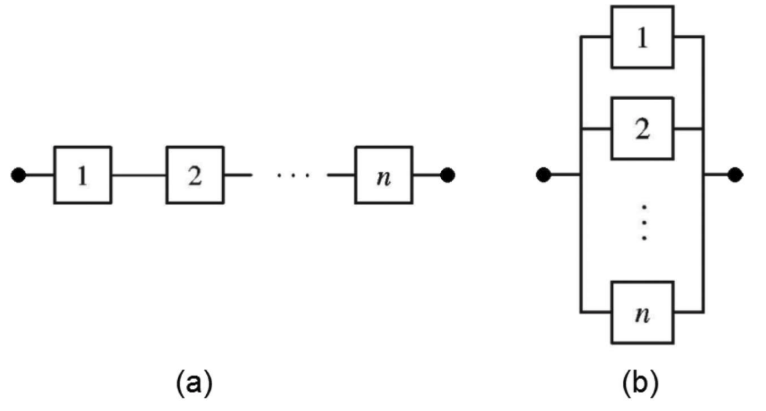

Figure 2.7: Examples of series and parallel configurations using RBDs (Callou *et al.*, 2014).

Specific equations to calculate reliability and failure rate of the whole system (R_S and λ_S respectively) can be found in literature (Rausand & Hyland, 2008; Rome Laboratory, 1993). In case of components connected in series:

$$R_S = \prod_{i=1}^{n} R_i \tag{2.11}$$

and

$$\lambda_S = \sum_{i=1}^{n} \lambda_i \tag{2.12}$$

Where R_i and λ_i are the reliability and failure rate of the individual components respectively. Similarly, in case of redundant (identical) components connected in parallel:

$$R_S = 1 - \prod_{i=1}^{n} (1 - R_i) \tag{2.13}$$

and

$$\lambda_S = \frac{n(\lambda)^{d+1}}{(n-d-1)(\mu)^d} \tag{2.14}$$

where μ is the repair rate of the component (1/repair time), n is the total number of redundant components and $n - d$ those required for the system or configuration to remain operational. $n - d$ is often indicated as k, in the so-called *k-out-of-n* configuration, a particular case of parallel redundancy in which at least k components, out of the total n parallel components available, must remain functional in order that the system keeps working.

As most systems are represented by a combination of both series and parallel configuration, in order to calculate the reliability and failure rate of the entire system, the ordinary procedure consists of considering sets of either all series or all parallel components, calculating the respective reliability or failure rate, and then grouping together the selections and treating them as single equivalent components. For instance, if there is a system with two components in series and one in parallel, in order to calculate the reliability of the whole system the first step consist in calculating the reliability of the two components in series, and then consider this as a single component connected in parallel to the third one.

After having discussed the basics of the methodology on which the characterisation model is built, the next section will introduce the foundations for the implementation of the second model, the one aiming at strategy optimisation.

2.4 Multi-objective optimisation

Nowadays, in engineering as well as in other areas, optimisation is of pivotal importance to any problem involving decision-making. In these problems several alternatives are usually available, and the *optimal* solution, in the wider sense of most suitable or convenient choice, is sought. Optimisation algorithms deal with the selection of the best combination of decision variables, as measured by one or more numerical functions, among those available. The measure of quality or goodness of the alternatives is described by an objective function or performance index (Chong & Zak, 2013).

The problem normally consists in using an evaluation function to assess the quality of a given solution, and then determining the values of the decision variables that either minimise or maximise the designated objective by applying a search algorithm. If any value for the decision variables is allowable the problem is *unconstrained*, otherwise, if one or more requirements or restrictions (constraints) have to be applied during the search for possible solutions the problem is *constrained* and the solutions which satisfy the constraints are referred to as *feasible*. In other words, solutions are to be found within an objective space where constraints limit the search, and anything within the space is a feasible solution. For this reasons, optimisation is also defined as the act of obtaining the best result under given circumstances (Rao, 2009). Generally, the space containing the solutions is referred to as *decision space*, whereas the space containing the evaluation of the solutions is referred to as *objective space* (Kok, 2014). A more generic term, used ambiguously for both decision and objective space, is *search space*. Decision and objective spaces, and the mapping between them, are illustrated in Figure 2.8.

If the problem involves only one objective (e.g. minimise the costs), it is a *single-objective optimisation*. However, when optimal solutions are sought with respect to conflicting or competing objectives (e.g. minimise the operational efforts while maximise the economical benefits), in which the improvement in one of the objectives possibly leads to worsening in another, these are generally referred to as *multi-objective optimisation* problems. In this case, the optimal value for the set of decision variables must not only satisfy eventual constraints, but also optimise a vector function constituted by all the individual single-objective functions. As a consequence, the optimal solution may not be unique because the simultaneous optimisation of all objectives is

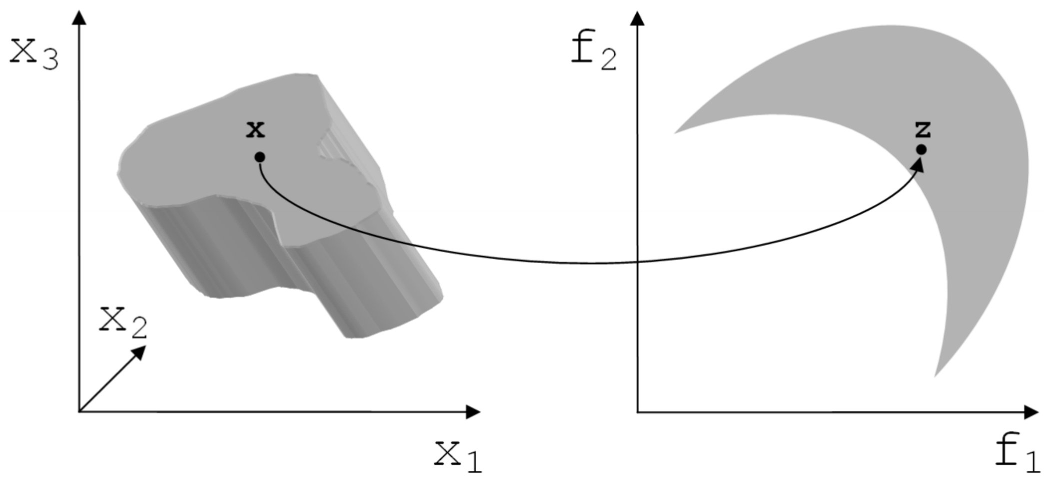

Figure 2.8: Representation of the decision space (on the left) and the corresponding objective space (on the right) in a multi-objective problem (Kok, 2014).

prevented by the nature of the problem itself. Thus, in this situation, rather than a single optimal solution a set of these, called *non-dominated*, are sought in the optimisation process. This set is constituted by those solutions that cannot be further improved with respect to one of the objectives without worsening at least with respect to another, and is better known as *Pareto frontier* or *Pareto front* and the solutions that constitute it as *Pareto optimals*. An example of dominated and non-dominated solutions, and Pareto frontier is shown in Figure 2.9 (Dufo-Lopez *et al.*, 2011). This set is commonly sought-after by decision-makers in order to find a series of ideal trade-off solutions with respect to all the competing objectives of the problem, and therefore have a range of possibilities to support the decision-making process according to the preferred criteria. In other words, trade-offs among different objectives can be prioritised according to the benefits brought to each objective. Furthermore, understanding the Pareto front, and defining its shape, also advises what kind of compromise exists between the competing objectives and what to expect in future improvements. Examples of these frontiers are shown in Figure 2.10 for different combinations of optimisation problems involving either minimisation or maximisation of two objective functions.

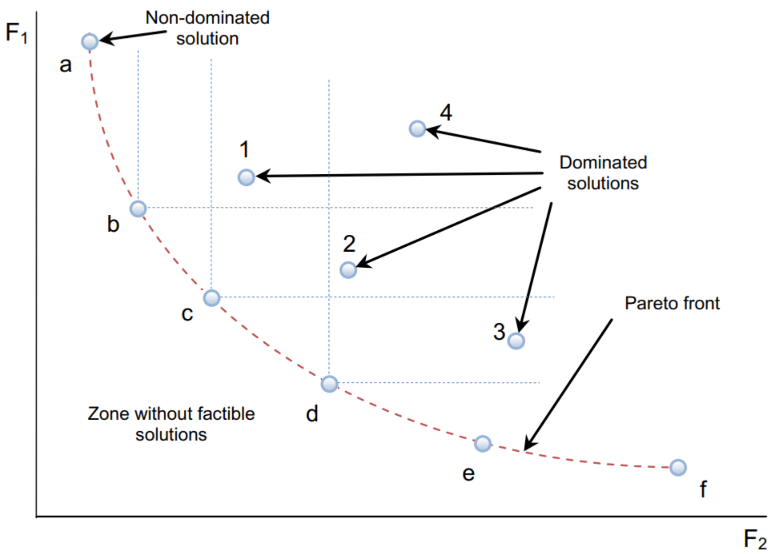

Figure 2.9: Example of Pareto frontier for a multi-objective optimisation problem involving two objectives which are both to be minimised (Dufo-Lopez *et al.*, 2011).

2.4.1 Heuristics

When dealing with relatively small or non-complex problems, the most immediate choice in order to find the best solution consists in performing an exhaustive search (i.e. evaluate all the possible solutions) and determine which one is optimal according to the pre-established objective(s). However, when the size or complexity of the problem grows, this approach may result impractical, or impossible to complete in a reasonable amount of time, due to the large number of parameters involved in the evaluation of the candidate solutions. Furthermore, for some problems (especially those involving real world models) the complexity is so high that it is impossible to guarantee that the implemented optimisation process returns the absolute optimal solution (Burke & Kendall, 2013).

As a consequence, specific procedures called *heuristics* need to be implemented. These aim at providing improved solutions with respect to the considered problem, but that cannot be guaranteed to be the absolute optimal due to the impossibility in recurring to complete and exhaustive searches across all the feasible alternatives.

According to the dictionary of computing (1996), a heuristic is defined as *"a rule of thumb, based on domain knowledge from a particular application, that gives guidance*

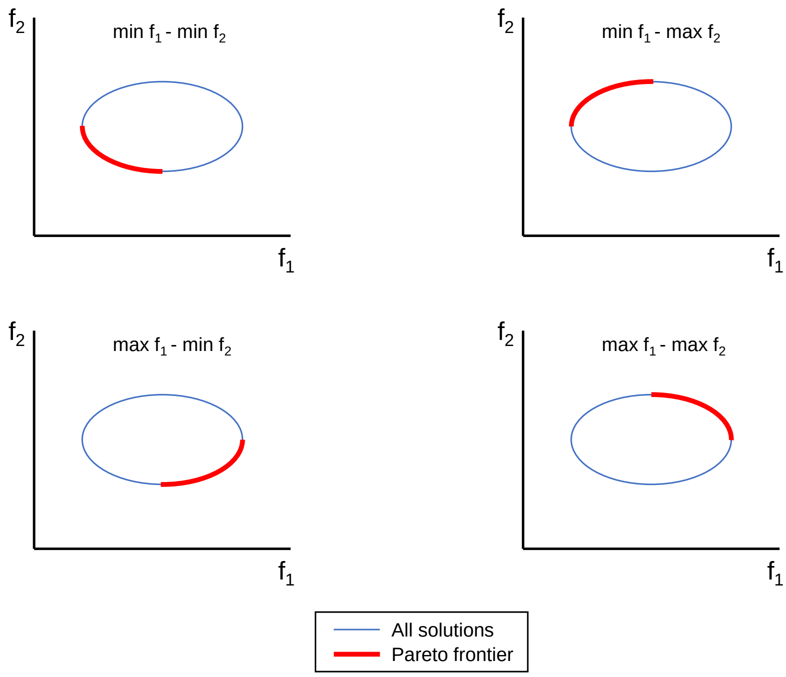

Figure 2.10: Examples of Pareto frontiers for multi-objective optimisation problems involving two objectives. Adapted from (Chong & Zak, 2013).

in the solution of a problem". Reeves (1993) defines a heuristic technique (or simply heuristic) as a method which seeks good (i.e. near-optimal) solutions at a reasonable computational cost without being able to guarantee optimality, and possibly not feasibility. In addition, it may not even be possible to state how close to optimality a particular heuristic solution is.

It is also useful to make a distinction between heuristics and metaheuristics. The former are specific to a problem, while the latter are general strategies or higher level optimisation procedures. For example, evolutionary algorithms are in general metaheuristics, whereas the specific genetic algorithms implemented in this work are heuristics for the specific problem of optimising the O&M procedures.

2.4.2 Genetic algorithms

In the last decade, evolutionary approaches have been the primary tools to solve real-world multi-objective problems (Konak *et al.*, 2006). Although a vast number of optimisation techniques and heuristics have been developed for solving different types of problems (Rao, 2009), e.g. particle swarm optimisation and neural networks, according to Baños *et al.* (2011) nature-inspired evolutionary algorithms are among the most diffused methods applied to renewable energy optimisation. Within this category, a growing number of research papers pursue the optimal design and operation of renewable energy systems by using an heuristic optimisation method called *genetic algorithms (GAs)*. Among the reasons of this success, simplicity in the formulation of the problem to be solved, re-usability for a series of similar problems once that the algorithm has been defined, and the lack of necessity of knowing the solution space, can be cited (Fabritius, 2014).

Genetic algorithms were initially developed by John Holland in the mid 1970's (Holland, 1975). These are adaptive search procedures which mimic biological processes of selection and evolution to solve both constrained and unconstrained optimisation frameworks. Based on an analogous operating principles, GAs consider a population of solutions which through a series of steps evolve over time to reach the optimal solution. In a manner similar to how biological species adapt to their environment and preserve beneficial traits between subsequent generations, a GA uses the information of how solutions perform in order to guide the search through the search space. Thus, they can be used in complex single-objective and multi-objective problems in order to generate solutions that have evolved towards the optimal result (Man *et al.*, 1996). A typical GA works according to the flowchart shown in Figure 2.11. To begin, a population, a group of individuals, is created at random. In this, each individual represents a candidate solution to the decision problem and it is encoded using binary code or other representations (Aggarwal & Goswami, 2014). Despite several seeding strategies exist (Mirshekarian & Süer, 2016), typically, in binary code, the initialisation consists in randomly assigning a 0 or 1 to each one of the bits of the individual, respecting eventual pre-established feasibility criteria. Each individual is often referred to as a *chromosome* or *genotype*, and the information contained in each individual is directly linked to the values of decision variables for the investigated problem. Secondly, each individual is evaluated according to its suitability with respect to one or a series of predefined objectives, and a score (*fitness*) is assigned to it. In other words, evaluation functions are used to convert the genotype into a phenotype. Individuals are assigned a probability of selection proportional to this fitness, which is used to select pairs of individuals. These pairs are then recombined through crossover algorithms to generate the new individuals of the population. Finally, the new individuals are randomly mutated to refine local searches in the investigated domain. This process is repeated until specified termination conditions are met or the maximum number of generations is reached. These typical phases of a GA are graphically represented in Figure 2.12. In this way, over successive generations, the population evolves towards a set of improved solutions. Optionally, a restricted number of individuals with the best fitness values, called *elite*, can be preserved from one generation to another without being subjected to the genetic operators.

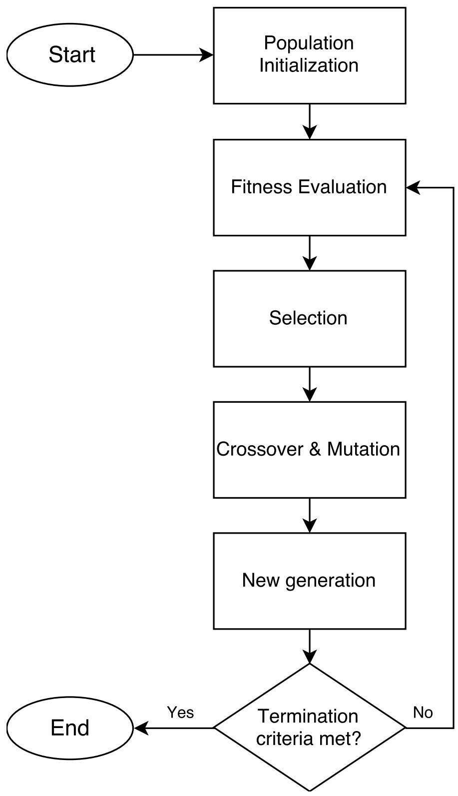

Figure 2.11: Flowchart of a genetic algorithm.

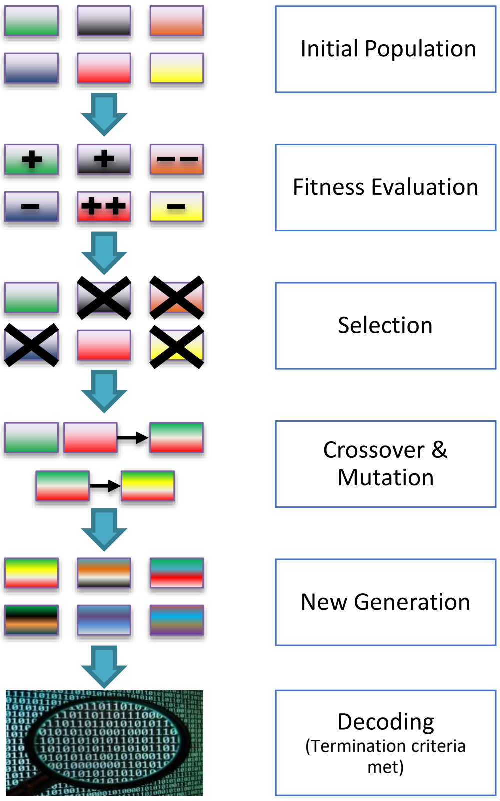

Figure 2.12: Graphical representation of the typical phases of a genetic algorithm. Each individual in a new generation is given from repeated selection, crossover and mutation.

2.4.3 Optimisation models for offshore renewables

A number of works aiming at the optimisation of renewable energy systems can be found in literature (Bajpai & Dash, 2012), most of them involving Multi-Criteria Decision Making (MCDM) techniques (Pohekar & Ramachandran, 2004) and multi-objective optimisation by using evolutionary algorithms (Fadaee & Radzi, 2012). Some of these models have also addressed O&M related problems, like that of spare parts allocation (Marseguerra *et al.*, 2005), planned interventions (Javanmard & Koraeizadeh, 2016) and scheduling and routing of vessels to perform maintenance activities within an offshore wind farm (Dawid *et al.*, 2018) or across multiple wind farms (Raknes *et al.*, 2017). Abdollahzadeh *et al.* (2016) propose the use of a multi-objective particle swarm optimization algorithm, coupled to a three-phase discrete-event simulation, to optimise the reliability thresholds of pre-established maintenance strategies for generic (onshore or offshore) wind farms. Similarly, Marseguerra *et al.* (2002) propose an approach which couples Monte Carlo simulation and genetic algorithms for determining the optimal degradation level beyond which preventive maintenance has to be performed. The choice of a coupled approach is supported by the fact that GAs reduce the number of evaluations needed to achieve satisfactory results. These, in fact, gradually focus on successful solutions, reducing the need to evaluate unsatisfactory alternatives. Jin *et al.* (2013) proposes a multicriteria (cost and reliability) optimisation model, based on genetic algorithms, to design and operate a wind-based distributed generation system.

The advantages of combining the complementary strengths of simulation and optimisation models in a mixed methods approach have been described and discussed in Glover *et al.* (1996), and demonstrated with specific application to improve sustainability of road transportation (Clausen *et al.*, 2012) and even in the offshore sector to improve the installation of offshore wind farms (Barlow *et al.*, 2018).

However, when computational models for O&M of offshore renewables were analysed in the previous Section 2.2, most of these aimed at the characterisation of the ORE farm key performance indicators (KPIs), leaving room for the subjective interpretation of the outcomes and the selective proposal of eventual improvement measures. Therefore, the optimisation of the O&M strategy and an eventual support in the selection of the optimal assets composition is assumed as a direct consequence of the corrective measures following the KPIs analysis. To the best of the author's knowledge, a model for the direct optimisation of the complete O&M strategies and assets management is unknown. According to Shafiee (2015), multi-objective (multi-criteria) maintenance strategy selection is an underexplored area in the offshore wind energy sector.

Nonetheless, other models are explicitly orientated towards an optimisation framework that, once implemented, leads automatically the search towards the optimal value for the selected decision problem. A number of models addressing only one of the logistics management related aspects, or decisional problems in other contexts for the improvement of offshore renewables in a specific optimisation model can be found in literature.

Gonzalez *et al.* (2013) investigated a method to maximize the profitability of an offshore wind project through the optimal micro-siting of the devices, achieved by splitting the available marine area in a grid and optimise each domain individually by means of a specifically implemented genetic algorithm. Similarly, Pillai *et al.* (2018a) used a particle swarm optimisation framework to evaluate the effects of different layouts on energy production and costs, and as a result on the levelised cost of energy, of an offshore wind farm. In the same work, further examples of wind farm layout optimisation using other techniques (e.g. viral based optimisation, pattern search, mixed-integer linear programming, Monte Carlo method and random search) are reported. Pillai *et al.* (2018b) also investigated the use of a multi-objective genetic algorithm in order to find the optimal design for the mooring system of a generic offshore renewable device by minimising the breaking load and material cost simultaneously. Similarly, González-Longatt *et al.* (2012) used the same technique (genetic algorithms) in order to find the optimal electrical network for offshore wind turbines by taking into account the costs of transformer, substation and and power cables and the efficiency of their configuration. Pillai *et al.* (2015) investigated the same problem, but representing it as a number of sub-problems to be solved using a combination of heuristic algorithms and a more robust approach based on Mixed Integer Linear Programming (MILP). A MILP framework is used also by Irawan *et al.* (2017) in order to build an optimisation model to find the optimal schedule for maintaining the turbines in an offshore wind farm, as well as the optimal routes for the crew transfer vessels together with the number of technicians required for each vessel. Dahmani *et al.* (2017) considered both the reliability and cost of an offshore wind farm architecture in order to optimise both its topology and electrical network layout by using a genetic algorithm approach.

Fonseca *et al.* (2014) compare the performance of three methods (genetic algorithms, Dijkstra's algorithm and ant colony optimisation algorithm) for the determination of the cheapest path between different wind parks for maintenance. Similarly to the work presented in this thesis, Barlow *et al.* (2018) integrate two modelling approaches to yield a mixed-method framework and decision support tool that improves logistical decision-making, but to be used to plan the installation of an offshore wind farm rather than its operation.

Chapter 3

Characterisation and optimisation models

Contents

This Chapter is divided in two main sections in order to describe the methodology adopted in this work, providing the structure of both the characterisation and optimisation models implemented.

First, Section 3.1 presents the characterisation tool developed in order to evaluate the key performance indicators of the ORE farm, with particular consideration of the O&M strategy. The required inputs, mechanisms and constraints considered, and outputs obtainable from the characterisation tool are presented. This model is implemented with the overarching goal of providing ORE farm owners or operators, and decision-makers in general, a method to evaluate the effectiveness of their assets. This model can be used prior to the installation of the farm in order to assess the viability of the project, as well as during the operational phase in order to support the strategic and tactical planning, i.e. medium to long term decisions.

Second, Section 3.2 details the optimisation framework by introducing the different approaches adopted. This section describes the evaluation functions implemented and related inputs, and providing examples of outputs and approach selection criteria. This framework constitutes a *surrogate model* (or metamodel) that has been built and calibrated according to the results and trends identified with the characterisation tool. This is able to evaluate candidate solutions in a simpler and quicker way, bypassing the computational limitations of the characterisation model, and orienting the search for improved alternatives. In this way numerous possibilities are explored and further insights gained. The main goals of this model are the automated proposal of suitable alternatives to the current combination of assets, as well as the establishment of a search procedure to find solutions beneficial for the viability of the project. Similar to the previous tool, also this model provides support in the medium to long term time horizon.

To some extent, this model can be classified as an *emulator*. According to the definition of OHagan (2006), an emulator is a statistical approximation of a mathematical model or computer program, called *simulator*. An emulator is generally used to save time in comparison to the repeated use of the simulator, for instance in a sensitivity analysis. Similarly, Sacks *et al.* (1989) uses the term *predictor* to indicate a tool which provides a response at untried inputs in place of the computationally expensive codes on which it has been tuned.

3.1 Characterisation model

The first tool described is used to characterise the performance of the ORE farm in terms of reliability, availability and maintainability. It will be hereinafter indicated as "characterisation model", "Monte Carlo tool", or "UoE/JFMS tool" (because conceived and developed within a collaborative partnership between the University of Exeter and James Fisher Marine Services Ltd.) indistinctly. This section describes in detail the offshore O&M characterisation tool implemented. Specifics are provided on the input variables required to start the simulations, together with the mechanisms and constraints that regulate their evolution with time. In addition, a full description of the outputs obtained and their use in the strategic planning is presented.

According to the literature review discussed in Chapter 2, a time domain approach based on the Markov Chain Monte Carlo technique discussed in Sections 2.3 and 2.3.1 has been adopted to develop the O&M characterisation tool presented in this work. Although a number of alternative suitable techniques exist, this approach has been selected due to the ease of implementation combined with the effectiveness in capturing and interpreting the operational aspects of an ORE farm, including external factors such as maintenance vessels and weather. Furthermore, this approach provides a degree of insight and flexibility which is essential to capture the nuances of operational activities (McMillan & Ault, 2007) and has been successfully deployed by industry to a wide range of projects.

The implemented model seeks to exploit the MetOcean data (hindcast or synthetic) of the location where the offshore farm is or will be located, together with all the specifications of the projects in terms of devices, vessels and maintenance strategies, in order to obtain a series of results that can be analysed in an iterative procedure to characterise the dynamics of the farm and optimise the planning actions. To do so, the model takes into account a large number of inputs, mechanisms and constraints according to the Structured Analysis and Design Technique (SADT) (Mylopoulos, 2004), a computational practice used to describe complex systems and which operates on the general basis shown in the diagram in Figure 3.1.

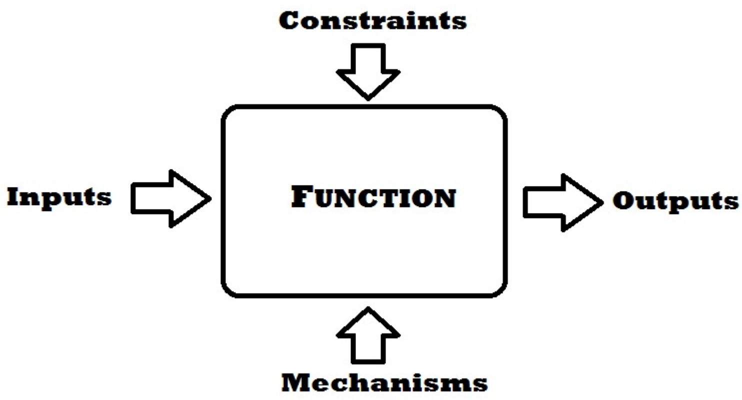

Figure 3.1: Graphical representation of SADT. Adapted from Mylopoulos (2004).

A summary of the inputs, constraints, mechanisms and outputs, considered within the SADT framework but specific to the problem presented in this section, is graphically represented in Figure 3.2. These have been identified in the reviewed studies and after discussion with industry representatives, and been selected according to their relevance for an effective characterisation of the ORE farm and their influence on the profitability of the project. The figure shows the main inputs required on the left-hand side, the logistical and meteorological constraints on the top, the considered maintenance regimes and reliability design mechanisms on the bottom, and the high level outputs on the right. These outputs are used to obtain an overview of the reliability, availability, maintainability and profitability of the ORE farm. A detailed assessment on the performance of the farm is thus obtained as a result of the simulation.

The number of factors considered indicates not only the complexity of the model, but also of the level of detail involved. Considering the difficulties in retrieving data, the model has been developed in such a way to demand only a minimum level of inputs in order to run a basic simulation. However, the more input data is used, the more detailed and accurate will be the results. In other words, the flexible framework of the model allows various levels of fidelity depending on the available data.

All the individual inputs, constraints, mechanisms and outputs considered in this tool will be introduced in the following subsections.

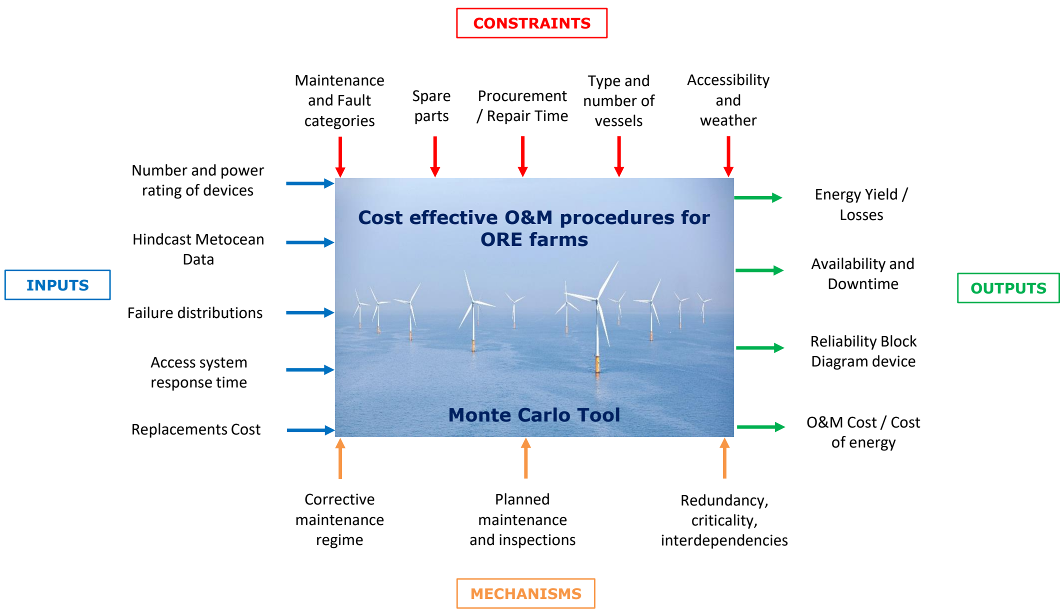

Figure 3.2: Scheme of the O&M characterisation model implemented in this work according to the SADT framework. Adapted from Karyotakis (2011).

3.1.1 Inputs

This section describes the main data the model requires to perform the simulation. These are grouped in inputs regarding the power performance of the ORE farm, weather data of the farm location, reliability data of the devices and maintenance access systems.

3.1.1.1 Number and power rating of the devices

In order to estimate the energy yield of the ORE farm, the number of devices that constitute the offshore farm, but not their layout in the ORE farm/array and interdevice distance, must be specified together with the energy converter's reference power performance. This last is used to express the energy produced by a device according to the instantaneous amount of available resource. It is a power curve in the case of an offshore wind turbine (OWT) and a marine current turbine (MCT); and a power matrix in the case of a wave energy converter (WEC).

Power curves can be retrieved from an external source (e.g. provided by manufacturer) or specifically created from the values for cut-in, cut-out and rated speed by using e.g. the least square method, one of the methods described in Kazemi & Goudarzi (2012), according to the equation:

$$P_v = \frac{P_{rated} \cdot (v^2 - v^2_{cut-in})}{(v^2_{P_{rated}} - v^2_{cut-in})} \tag{3.1}$$

Where P_v is the power output estimated for the fluid velocity v (between cut-in speed and the rated power speed) and P_{rated} is the power rated of the device.

Numerical wave energy capture models, based on hydrodynamic modelling, can be used to estimate the power matrix of a WEC (Babarit *et al.*, 2012); however, unlike for wind or tidal horizontal turbines, due to the lack of convergence on the power take-off system for WECs there is not a standard method for the direct estimation of the power matrix.

3.1.1.2 MetOcean data

The model uses the time-series of the resource data, referring specifically to wind, wave and current characteristic parameters. These are principally required in order to estimate the energy production of the farm and further to calculate the accessibility of the maintenance vessels, given their MetOcean limits and weather data. This time-series data can either be hindcast or synthetic forecast data. No restrictions exist on the maximum or minimum length of the timestep that separates two consecutive values. Nonetheless, since the model assumes stationarity between two consecutive values, too large timesteps would cause inaccurate weather related calculations.

In the case of offshore wind devices characterisation, the optional use of wind speed extrapolation as a consideration of the wind shear at the site is allowed within the model. In order to account for the difference in wind speed between the height of measurement and the nacelle height, the logarithmic wind profile law is used (Manwell *et al.*, 2009):

$$v_z = v_{ref} \cdot \frac{\ln(\frac{z}{z_0})}{\ln(\frac{z_{ref}}{z_0})} \tag{3.2}$$

where v_z is the wind speed to be extrapolated at nacelle height z, z is the nacelle height, v_{ref} is the wind speed measured at reference height, z_{ref} is the reference height, z_0 is the roughness coefficient length (typically 0.0002 m in open sea).

3.1.1.3 Failure distributions

The failure rates of the selected components of the device, which can be collected through the procedures described in Section 2.1.2, are used to estimate the number of corrective interventions. The model accepts either exponential or two-parameter Weibull failure distributions. In the first case, a constant value for the failure rate in failures/year has to be provided. In the second case, scale and shape parameter characterising the failure distribution have to be provided; two options exist in this case. The first option consists in providing only two values (one scale parameter and one shape parameter) for the entire lifetime of the component. The second option consists in providing a set of six values (three scale parameters and three shape parameters) in order to shape the failure rate of the component according to the bathtub curve introduced in Figure 2.5. In this way it is possible to take into account different failure behaviours (e.g. the early stage failures, random failures and degradation failures shown in the bathtub curve in Figure 2.5) depending on the lifetime of the component. In this case, attention must be paid at the interpolation between two contiguous areas in order to guarantee continuity in the failure rate over time.

Apart from these values, further circumstances, such as weather conditions and the marine environment, can lead to a decrease or increase of the failure rate. To take these considerations into account, the model incorporates optional elements of reliability assessment (discussed in Section 2.1.2) to take into account eventual power rating and environmental stress factors, in order to adjust failure rate values. The model allows for these adjustments by using the physics-based model proposed by Davidson (1994) which has been embraced in a number of works (Karyotakis, 2011; Santos *et al.*, 2015). It consists of adjusting the failure rates of the different components of the device by applying appropriate environmental and power rating factors as shown in Equation (3.3).

$$\lambda_C = \lambda_B \cdot \pi_E \cdot \pi_{PR} \tag{3.3}$$

where λ_C is the failure rate of the selected component; λ_B is the base failure rate (extracted from database or provided by manufacturer); π_E is the environmental adjustment factor (to take into account eventual effects of the offshore environment on the reliability of the component); π_{PR} is the power rating adjustment factor (to take into account eventual effects of higher loads with respect to rated values on the reliability of the component). The environmental adjustment factor π_E can be established based on comparative loading conditions with other environments (Thies, 2012) for which there is certainty about the values of the failure rate (e.g. dry conditions, controlled environments, etc.), whereas the power rating adjustment factor π_{PR} can be established based on its relationship, if known, with the percentage of the component nominal rating (Davidson, 1994). It must be noted that the use of generic environmental and load adjustment factors introduces a higher degree of uncertainty in the reliability assessment since loading conditions, and consequently failure frequency, may vary between benign and dynamic deployment sites (Khalid *et al.*, 2016). This limitation can be eliminated by the acquisition of detailed site-specific reliability data for individual failure modes. However, this expansion of data bank is usually not undertaken since it is capital intensive.

At this point it is worth noting that the use of reliable failure data, as well as the correctness and accuracy of the reliability assessments, are beyond the scope of this work. Instead, the tool implemented mainly aims at providing the modelling capabilities needed to correctly interpret and account for all the inputs, including the reliability data, assuming that these are representative of the offshore device under analysis.

3.1.1.4 Vessels mobilisation and response time

A number of parameters, among which the fuel cost and the exact time needed by each access system in order to reach the offshore farm from the maintenance port, are established using Mermaid, the project planning tool for the risk mitigations on offshore procedures proprietary to Mojo Maritime Ltd. mentioned in Section 1.2. This provides a detailed day-by-day transit time (in hours) for each day of the year during the simulated period, according to the MetOcean conditions for that day and all the capabilities (MetOcean limits) of the vessel. In order to obtain these values a Mermaid analysis must be conducted prior to the use of the characterisation model, in which a task representative of the maintenance operation, including the time to prepare and assemble maintenance crew and equipment in port (mobilisation), must be set up.

The use of Mermaid permits a greater degree of detail and, provided that reliable inputs are used, a reduction in the uncertainty on the accessibility of the offshore farm. However, if for any reason Mermaid is not available, a fixed response transit time for any day of the simulation can be used instead.

3.1.2 Constraints

This section details the restrictions to the system that can be modelled with the characterisation tool.

3.1.2.1 Maintenance, fault and consequence categories

Maintenance categories have to be specified for both access systems and components, in order to allow the maintenance operation only if there is a match between the two categories. These have to be specified by the user, and can be used to distinguish between major or minor maintenance interventions, heavy or small components and vessels requirements. Example of these categorisations can be found in Dalgic *et al.* (2013) and Rademakers & Braam (2002), otherwise can be prepared *ad hoc* for each specific project. This serves to take into account the capabilities of the vessel with respect to size, weight and maintainability of the components.

On the other hand, fault categories are used to classify the effects of the failure of a component in terms of significance of the maintenance intervention, impact on costs (including disruption costs) and crew needed to solve the problem. An example of these quantification can be found in the consequence classes established according to the DNV-GL certification (DNV-GL, 2015), used in order to measure effects of the failures on production and assets. Similarly to the maintenance categories, these can be established *ad hoc* for each specific ORE project.

An example of maintenance and fault categories, and the way in which these can be linked, is illustrated in Figure 3.3.

Maintenance Category		Fault type Category		Crew Size	
Description	No.	Description	No.	Description	# Technicians
Heavy comp., ext. crane	1	Major replacement, very high costs	1	Large	6
Heavy comp., ext. crane	1	Major repair, high costs	2	Large	6
Heavy comp., ext. crane	1	Medium repair, medium costs	3	Large	5
Heavy comp., int. crane	2	Medium replacement, medium costs	4	Medium	4
Heavy comp., int. crane	2	Medium repair, medium costs	5	Medium	4
Heavy comp., int. crane	2	Small repair, low costs	6	Small	3
Small parts, Not man carried	3	Medium repair or replacement, medium	7	Medium	4
Small parts, Not man carried	3	Small repair or replacement, low costs	8	Small	3
Small parts, Man carried	4	Small repair or replacement, low costs	9	Small	3
Small parts, Man carried	4	Small repair, consumables	10	Very Small	2
Manual Reset	5	Manual Reset only, no added costs	11	Very Small	2
Remote Reset	5	No crew, no costs	12	No crew	0

Figure 3.3: Example of maintenance and fault categories. Adapted from Dalgic *et al.* (2013) and DNV-GL (2015).

3.1.2.2 Procurement and repair time

These values are needed in order to assess the amount of time that each maintenance intervention requires and, according also to the response time of the access system, the total period that the device will eventually remain in downtime as a consequence of a failure. The repair time indicates the required time (in hours) to execute the repair or replacement of the selected component, while the procurement time indicates the required time (in hours) to find a spare part for the selected component and make it available for the maintenance crew. It can be set to zero if this time is negligible with respect to the repair time or if the maintenance intervention is only a repair (procurement of spares not needed).

3.1.2.3 Spares in stock and intervention costs

The number of spare parts available in stock is needed in order to introduce sequencing rules on the replacement process, which can start only if the required part is in stock (otherwise the procurement time introduced in the previous section has to be added). The latter represents the costs associated to the repair or replacement of the considered component, and are used to take the costs of the maintenance interventions into account in the economic modelling of the farm.

3.1.2.4 Fleet information

The type and number of vessels present in the fleet (both rented or purchased) are taken into account to respect the sequencing rules during simultaneous downtimes. In this way, maintenance operations which require a specific access system can take place only if there is at least a unit of that kind available at that particular timestep, otherwise this has to be delayed until when the unit is available (provided that the MetOcean conditions are still suitable). If related properties are adequately specified, helicopters may also be considered in the analysis.

In order to include the difference between rented and purchased vessels, the corresponding daily and standby rates must be specified. The daily rate is the cost incurred for each working day, i.e. each 24-hour period during which a maintenance intervention is being performed, therefore it may be set to zero if the access system is a property of the farm and does not need to be chartered every time it is needed. The standby rate is instead the fee incurred for each non-working day of the access system, representing expenses like the mooring and port related fees, and may be set to 0 if the vessel is rented and therefore these expenses are included in the charter cost. In addition to these entries, the mobilisation cost of each access system can be specified in order to account for the cost of preparing the vessel and its crew each time that this is mobilised for a maintenance intervention. These entries, under appropriate considerations and in conjunction with the other inputs and constraints, can be used to model the typical contractual arrangements for offshore vessels, e.g. voyage charter (spot market) or time charter. The main charter strategies are summarised in Figure 3.4 (Dalgic *et al.*, 2013). However, if a vessel is purchased, the capital expenses of this choice must be added separately to the final maintenance costs. Furthermore, it is assumed that the costs are known before the simulation, therefore the volatility of the cost to charter a vessel in the spot market is not captured.

If not calculated by using Mermaid (Mermaid, 2015), a fixed fuel cost can be considered to account for the fuel needed for one single transit from the O&M port to the offshore location. A daily crew member cost, representing the average price for each crew member for each day of intervention, has to be specified to calculate the labour costs of each maintenance intervention. This last value can be set to 0 if the crew costs are included in the charter contract.

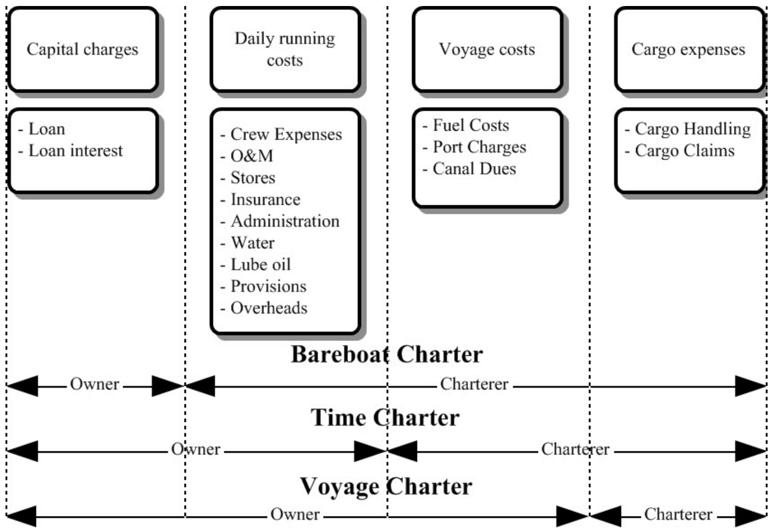

Figure 3.4: Example of cost distribution for different vessel charter strategies (Dalgic *et al.*, 2013).

Finally, a last parameter (indicated in this work as *seasonality*) can be specified in order to restrict the availability of the considered access system to specific periods, e.g. summer months, in order to further refine the implemented charter strategy. Nevertheless, the necessary personnel is assumed to be always available when needed, i.e. there are no additional sources of delay due to the procurement of a suitable maintenance crew.

3.1.2.5 Accessibility and weather

Accessibility for maintenance is permitted only if a minimum weather window for that maintenance task is available. This is calculated starting from the MetOcean data and considering the operating limits of the required access system, its response and transit time previously assessed as specified in Section 3.1.1.4 and the time required for maintenance assessed as specified in Section 3.1.2.2. Besides, in order to account for the fact that while some operations can be performed indifferently during the day or overnight others require daylight, this possibility has to be specified among the properties of both the maintenance access systems and the components. Therefore, the model calculates the sunrise and sunset time for every day of the considered period in the selected location. The maintenance overnight is then allowed only if the conditions to operate in absence of daylight are satisfied both on the considered access system and failed component, otherwise the operation is postponed until there is daylight.

3.1.3 Mechanisms

This section details the mechanisms considered in the characterisation model and according to which the system (i.e. the offshore farm) evolves with time.

3.1.3.1 Corrective maintenance regime

The failures and the consequent downtime of each device are generated according to the input parameters explained in the above sections and by using the methods based on Markov Chain Monte Carlo simulation described in Section 2.3.1. This constitutes the background for the corrective maintenance operations due to unexpected faults. Every corrective action following a maintenance intervention restores the component to an as good as new state (perfect maintenance) as described in Section 2.1. Nonetheless, this effect is noticeable only if failure rates varying with time are considered. If constant failure rates are used, minimal maintenance restoring the component to an as bad as old state is considered. All interventions are carried out in one go, avoiding multiple journeys and operations on multiple devices.

3.1.3.2 Planned maintenance and inspections

The model takes into account the period of curtailment due to preventive maintenance operations, scheduled before any possible incidence or unexpected failure. Planned interventions have to be indicated before the beginning of the simulation by specifying how long the operation will take, if the device(s) will have to be shut down (and consequently not produce energy) during the intervention, on which component the task is to be performed, on how many devices among those in the ORE farm, and on what date the intervention will start. Total time required for the planned task and date of completion will be calculated accordingly. The timesteps associated to prescheduled interventions are distinguished from those related to corrective maintenance (null production due to an unexpected malfunction of the system) in the final assessment. Finally, also the preventive maintenance regime restores the selected component to its initial reliability values (perfect maintenance) provided that variable failure rates are used.

3.1.3.3 Components information

A range of information on the components that constitute the device and their configuration (in series or in parallel) in the system is required for the analysis. Firstly, it is possible to group several components as belonging to the same subsystem. For each component, in addition to the information described in the previous sections, it is necessary to specify whether this is critical (its failure determines the non-functionality) for the subsystem to which it belongs. Analogously, for each subsystem, its criticality with respect to the entire device must be identified. In this way, in order to correctly estimate the energy loss in case of failure, the downtime of the entire device is determined only when one of its critical subsystems fails, which in turn fails only if one of its critical components fails.

Eventual redundant items of the same type can be added to each component, together with the minimum number necessary to keep the subsystem to which these belong operative (*k-out-of-n* components).

Another mechanism considers the possibility of modelling depending components and inter-depending failures (Fleming *et al.*, 1986). Therefore, it is possible to establish a link between two components, in order to trigger the failure of one of them if the other one fails. This link, as graphically illustrated in Figure 3.5, can be unidirectional (component A fails if the component B fails but component B remains functional if component A fails) or bidirectional (if component A fails component B fails too and vice versa).

The mechanism can be extended to model the dependency among more than two components in order to produce cascading failures. In addition, instead of a direct failure as a consequence of another fault, it is possible to model a positive or negative dependency. In a positive dependency there will be an increase in the failure rate of a component (but it will remain operational) as a consequence of the failure of another component, whereas in a negative dependency there will be a decrease in the failure rate of a component as a consequence of the failure of another component. In this case, the percentage variation of the failure rate, due to the failure of the other component on which it depends, must be specified among the inputs.

Condition-based maintenance is not modelled since one of the aims of this work is to reduce the reliance on condition monitoring devices and SCADA instruments, whose

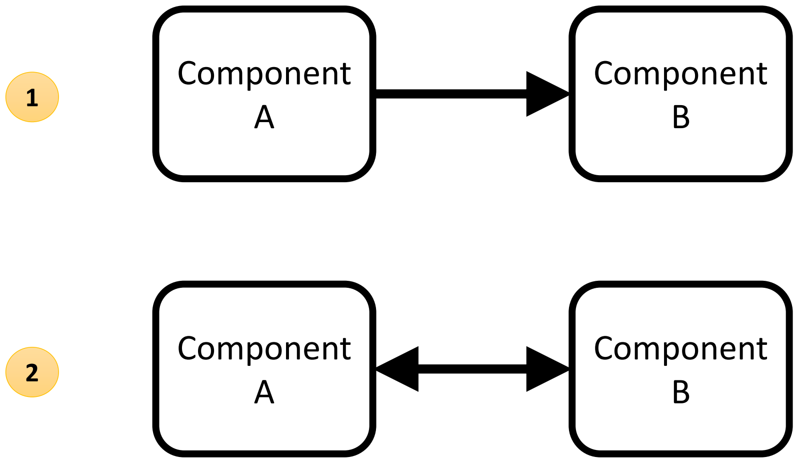

Figure 3.5: Example of links between components in the characterisation model. In a unidirectional link (1) the state of A affects B but the state of B does not affect A, whereas in a bidirectional link (2) the state of either affects both.

installation, even if able to potentially prevent undesired downtimes and have a net positive impact, inevitably increases the capital expenditures and complexity of the project. In this case not only the variables to be measured and the technical specifications of the sensors must be determined, but also their affordability, maintenance plan and calibration procedure. In addition, the eventual probabilistic modelling of condition-based maintenance, by simulating the detection of failure by means of e.g. hidden Markov models (Dawid *et al.*, 2015), would introduce an additional source of complexity, and possibly uncertainty, on the obtained results. Nevertheless, a complete review of mathematical and optimisation approaches to model the stochastic deterioration process of the device, and in turn influence the condition-based maintenance strategies, can be found in Alaswad & Xiang (2017).

Finally, it is possible to further refine the number of crew technicians required for the maintenance of each component, by adding or removing crew members to the crew size previously established through the use of maintenance and fault categories discussed in Section 3.1.2.1.

3.1.4 Outputs

The results of the simulations analyse the different options in terms of productivity, reliability, availability and maintainability of the farm, and can be used by the decision maker or operator of the farm to compare different maintenance strategies. These outputs include, but are not limited to:

- *Preliminary resource assessment*: resource distribution plot and histogram (wind and currents); annual and monthly variations (wave height, wave energy period, wave power density); energy distribution matrix and scatter diagram (waves); rose diagram (wind, waves, currents);
- *ORE farm performance*: Energy delivered and lost, where the latter is distinguished between energy lost due to scheduled maintenance tasks or inspections and energy lost due to unexpected failures (corrective maintenance); Time-based and energy-based availability of every device and the entire farm;
- *Reliability of the ORE farm*: Number of failures, contribution to unavailability and contribution to total number of failures for each component; Occurrence/ Severity matrix showing the likelihood and consequence of each components failure; Reliability and mean time to failure (MTTF) of each component; Risk Priority Number (RPN), which allows for the prioritisation of the risks associated to each component as detailed below; Reliability Block Diagram (RBD) of the system, in order to provide a visual feedback of the introduced information about the device;
- *Economic model of the ORE farm*: Breakdown of the maintenance costs; monthly and annual analysis on energy produced, energy lost, revenue and losses; Cost of repairs and replacement for each component;
- *Statistical analysis of the results*: Convergence of the results over the simulations and results distribution (with P90, P50 and P10 probability exceedances) on energy produced, energy lost, revenue and losses, ORE farm failures and failures of each component; and
- *Summary of the results*: Average key performance indicators summarised in a text file and available for post-processing in MATLAB and Excel.

The Risk Priority Number (RPN) (Nune Ravi & Bantwal S., 2001) is a numeric assessment of the risk associated to a failure event, and allows the classification of each failure by assigning a number which expresses its Severity (S), Occurrence (O) and Detectability (D), through the expression $RPN = S \times O \times D$. In order to calculate it, the following construct is adopted. Starting from the assumption that the risk is usually quantified in terms of likelihood and consequence of a certain event, the likelihood has been compared to the frequency of the undesired event (number of failures) and the consequence to their effect on the power production (downtime). Under these circumstances, these values can be obtained associating the occurrence to the average contribution to the total number of failures (the more often a component fails, the higher its contribution to the total number of failures) and the severity to the average contribution to the downtime (the more downtime a failure causes, the higher is the seriousness of the consequences of that failure). Therefore, if these contributions are provided in a percentage scale, it is possible to calculate the occurrence and severity of each failure. The detectability could be assessed considering the likelihood of detection by a control apparatus within a condition-based maintenance regime. However, as mentioned in the previous section, although it could be possible to estimate this parameter in a separate model, the quantification of the RPN has been restricted to occurrence and severity in order to avoid the introduction of imprecisions in the evaluation of the detectability.

Examples of these outputs, according to the results obtained for a case study, will be presented and discussed in detail in next Section 4.1. A simplified flow diagram showing the different modules of the tool is illustrated in Figure 3.6.

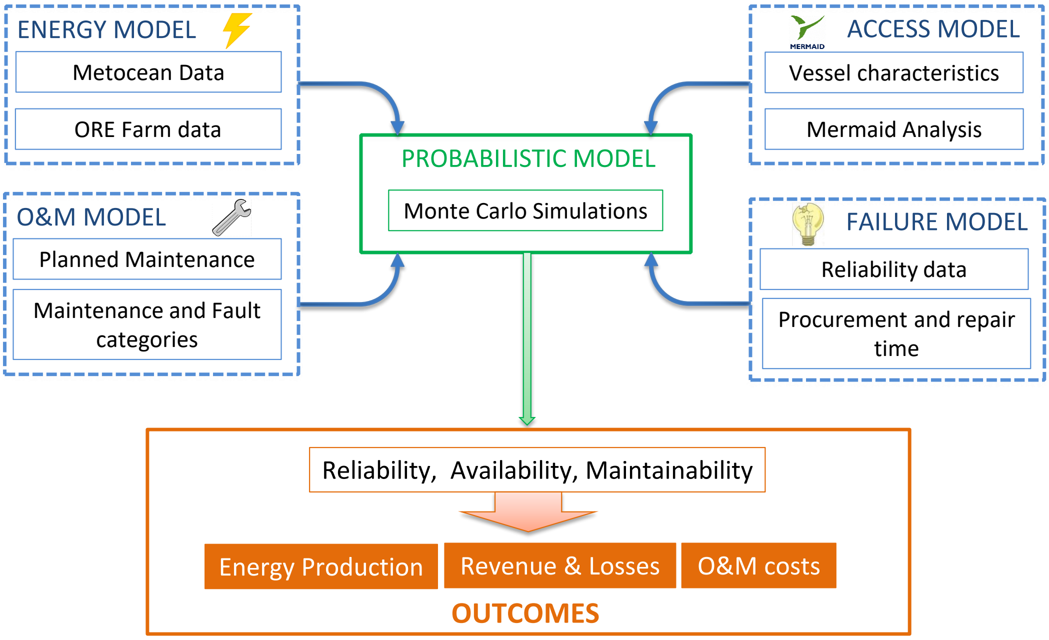

Figure 3.6: Graphical workflow diagram of the model of the O&M characterisation model implemented in this work.

3.2 Optimisation model

This section describes the offshore O&M optimisation framework implemented in this work. The use of multi-objective optimisation and genetic algorithms is proposed in order to automate the optimisation procedure needed to improve the O&M strategy of the ORE farm. Thus, a wide range of possible O&M solutions are explored using the implemented search procedures, removing the need of having possible alternatives to the initial O&M strategy proposed by a decision-maker.

The ideal in this case would be to couple an optimisation algorithm to a characterisation tool (e.g. the UoE/JFMS Monte Carlo model), thereby obtaining an accurate prediction of the KPIs with this last (the characterisation tool) and an automated progression towards improved solutions with e.g. the evolutionary algorithm. Unfortunately, due to computational limitations, often it is not feasible to couple an optimisation algorithm directly to a KPIs characterisation model, and therefore simpler, more time-efficient evaluation functions are required as a a viable alternative to the use of computationally expensive O&M characterisation tools. This allows for an effective combination of a quantitative method with a qualitative approach. Hence, a series of functions that estimate the desired performance indicators and assess the effectiveness of a solution over the others, avoiding the use of a KPIs characterisation model, are required. Furthermore, ORE farm owners and operators must face the challenge of dealing with finite maintenance resources (e.g. annual budget for O&M, purchasing the spare parts, insurance, and labor costs) (Shafiee, 2015). Thus, constraints have to be considered when the maintenance activities are planned and strategic decision made, and GAs are a simple and effective way of managing them.

Under these circumstances, and following the literature review in the previous Chapter 2, an approach based on genetic algorithms is chosen for the optimisation of the O&M assets. This technique is in fact widely used in the optimisation of renewable energy system, is computational efficient, allows for a good compromise between exploration and exploitation of the search space, and, above all, permits to combine the quantitative assessment technique described above (characterisation model) with a qualitative approach for an improved decision-making experience.

Firstly, the input parameters needed to initiate the optimisation procedure are described, and distinguished from the decision variables which define a O&M strategy, in

Section 3.2.1. Both input and decision variables are selected in such a way to provide a description of the ORE farm which is representative of its strategical and technical assets. The implementation of the objective functions, used to link the values of input parameters and decision variables to the outputs, and therefore used to assess the effectiveness of each proposed solution, are detailed in Section 3.2.2. The evolutionary algorithm approaches implemented in order to guide the search procedure and promote the automated optimisation of the O&M assets are described in Section 3.2.3. The outputs and results that are used to check the validity of the implemented model and give a more complete overview of the optimisation procedure are presented in Section 3.2.4. Finally, guidelines for approach selection and instruction on how to interpret the results for an effective decision-making process are provided in Section 3.2.5.

3.2.1 Inputs and decision variables

This section describes the inputs the genetic algorithms require in order to perform the optimisation. These have to be distinguished from the decision variables, i.e. those values whose attainment is the final objective of the optimisation procedure since they describe the assets configuration of the ORE farm, and for which there is uncertainty about the optimal value. Conversely, the input parameters provide information on the assets of the ORE farm but there is not uncertainty nor possibility of variation about their values because these define the properties of the assets.

Therefore, most of the input parameters needed for the characterisation of the ORE farm and discussed in previous Section 3.1 are used also for the optimisation model. Another set of inputs are provided as a result of the simulation performed with the characterisation tool, and are used to obtain a list of constants that are used to calibrate the objective functions. These will be described together with the various elements of the evaluation functions in Section 3.2.2.

When the optimisation of the strategic assets for the O&M of an ORE is required, the two main aspects on which an owner or operator can make decisions are the properties of the maintenance access systems (e.g. vessels and helicopters) and those on the device to deploy with its respective installed components. As a consequence, the strategic decisions addressed in this work are considered in terms of these two aspects. Accordingly, the *chromosome* representing each individual in the GA and the complete set of decision variables, and therefore the specific O&M strategy, includes:

- the number of units for each access system available for inclusion in the maintenance fleet;
- whether each of the access systems is limited to performing maintenance interventions during the day or can also perform them overnight;
- whether each kind of access system has been purchased or has to be chartered when needed for maintenance activities;
- whether each of the access systems have limited availability (e.g. available only during summer months);
- whether for each component of the devices redundant elements should be installed (compliant to technical constraints);
- whether for each component of the devices, a more reliable alternative should be installed (i.e. with a lower failure rate);
- whether for each component of the devices a repair or replacement intervention should be performable also overnight, in contrast to those components whose maintenance should be limited to periods with daylight; and
- whether for each component of the device there should always be a spare part available.

Thus, the information contained in each chromosome represents the decision variables of the stated problem. These values encase the number, type and respective properties of the access systems of the farm, as well as information and reliability properties of the components of the device. An encoding in which all decision variables are binary (either a 0 or a 1) is used to represent the presence, availability, or use of each of the options specified by the decision variables. An example of this representation is illustrated in Figure 3.7. Each property represents one of the considerations listed above, although the length of the chromosome may vary. The number of bits needed to determine the number of units of each access system depends on the pre-established maximum number of units to be considered, because the relationship that links the maximum number representable m with the number of binary bits needed n_{bits} is:

$$m = 2^{n_{bits}} - 1 \tag{3.4}$$

Therefore, with 2 bits it is possible to represent from 0 to 3 units, with 3 bits from 0 to 7, with 4 bits from 0 to 15 and so on. As a consequence, after the maximum number of units to be considered m is established, the formula used to calculate the number of bits needed is:

$$n_{bits} = \log_2(m + 1) \tag{3.5}$$

Once the maximum number of units considerable in the fleet is assessed, the remaining number of bits are established according to the number of access systems and components considered, and the population initialised using binary encoding as described in Section 2.4.2. In this phase, eventual feasibility constraints, that reflect logical or engineering requirements, are respected. These constraints impose:

- at least one unit of at least one access system in the maintenance fleet;
- not considering the properties of a vessel in the final solution if the vessel is not included in the fleet; and
- not assuming redundancy improvements if the pre-established possible number of redundant elements for a certain component is set to zero due to technical requirements.

The full relationships bringing together input variables and decision variables are thus described in the next Section 3.2.2.

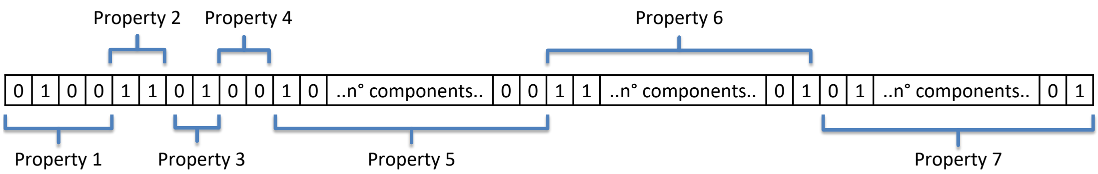

Figure 3.7: Example of representation in binary code for individuals (candidate solutions) in the GA. Each property refers back to the decision variables listed above.

3.2.2 Objective functions

Three objective functions are considered in this work in order to adequately represent the problem of improving the assets selection and logistics management of an ORE farm. To evaluate the fitness of each individual (i.e. potential solution), an accurate implementation of the functions relating the decision variables to the objectives is required. These, should accurately characterise the relationships between the input parameters and the decision variables of the problem. The overall aim is to obtain the optimal value for each of the decision variables according to the preference of the decision-maker. As already mentioned at the beginning of this Section 3.2, the use of the characterisation tool presented in Section 3.1 would be ideal in order to ensure that the evaluation of all the KPIs of the OWF is as accurate as possible, within the limits of the characterisation model itself. However, this coupling is not a straightforward task, especially if the characterisation tool is computationally expensive due to simulations involving one or more of the following factors: long time-series, a large number of devices, a large number of components considered in the taxonomy of the device, a large number of access systems. As a consequence, the implementation of a heuristic with substitutive objective functions (a surrogate model) is required to evaluate each individual with respect to each objective. Hence, based on observations with the previously implemented characterisation tool as described in Section 4.2, specific objective functions are built. Furthermore, these evaluation functions are calibrated and benchmarked in order to ensure predictions are as close as possible to those that would be obtained with the characterisation tool itself, validated independently and for which there is confidence in the model outputs, as illustrated in Section 4.2.2. Under these premises, based on the previous experiences with the O&M characterisation model, specific relationships are built in order to determine the fitness of each individual with respect to three objective functions. Considering the targets and performance parameter that an ORE farm owner or operator would generally be interested in, these are:

- a *cost* function;
- a *reliability* function; and
- an *availability* function.

While cost and availability are selected due to their obvious repercussions on the profitability of the project, the reliability, apart from being usually correlated to the availability, is also a common indicator used to establish targets when the maintenance of the farm is entrusted to external sub-contractors. For some of the contributions to the above objective functions (those whose formulation is more elaborated) the corresponding algorithm, as it has been implemented in Python 2.7, is reported in order to provide further elements for its understanding.

3.2.2.1 Cost objective function

The first objective function is used to assess the relative cost of a candidate solution compared to others, and it is referred to as the cost function. The considerations taken into account in order to build the contributions of the different elements of the chromosome to the cost objective function are hereinafter described and their formulation presented.

- *Cost per access system and ownership*: Generally, if a set of vessels belong to the farm the expenses due to mobilisations will be lower, the vessels will be more easily available for interventions (which reduces lost production) and the costs due to charters will be removed. On the other hand, the initial cost of purchase and the expenses related to port and maintenance fees of the vessels must be taken into account. As discussed in Section 3.1.2.4, in the characterisation tool the distinction between purchased and rented vessels is made by using standby rate and daily rate where required. When the access system is purchased and thus property of the farm, the daily rate is null, since it is considered that the farm operator does not have to pay to use the access system. A mobilisation cost for the individual operation is still required though, along with a standby rate to represent all the moorings, port and maintenance fees to maintain the access system. Alternatively, when the access system must be rented because it is not owned by the farm, the standby rate (e.g. all the expenses related to keep the vessel ready to work in port) is null (because it is the responsibility of the vessel owner), and there is a daily rate (together with the usual mobilisation rate). Therefore, a cost per access system $C_{A.S.}$ is established as the sum of all the applicable access system cost contributions (daily rate, standby rate, mobilisation rate, fuel, crew hourly cost). This is calculated as:

$$C_{A.S.} = C_i \cdot n_{units} + rate_{standby} + n_{int} \cdot (C_{mob} + C_{fuel} + C_{crew}) \tag{3.6}$$

if the access systems is purchased (bit representing the ownership of the access system in the chromosome is 1); and

$$C_{A.S.} = rate_{daily} + n_{int} \cdot (C_{mob} + C_{fuel} + C_{crew}) \tag{3.7}$$

if the access systems is chartered (bit representing the ownership of the access system in the chromosome is 0).

In these relationships, C_i represents the initial cost of the access system, n_{units} the number of units of that kind of access system considered in the current individual, $rate_{standby}$ and $rate_{daily}$ the standby and daily rate of the access system respectively as described in Section 3.1.2.4, C_{mob} the mobilisation cost of the access system, C_{fuel} the fuel cost for a typical transit from the maintenance port to the offshore location with the access system, C_{crew} the daily crew member cost with the access system, n_{int} the average number of maintenance interventions (both planned and unplanned) previously estimated with the characterisation tool:

$$n_{int} = (n_{ops_{corr}} + n_{ops_{prev}}) \cdot n_{devices} \tag{3.8}$$

where $n_{ops_{corr}}$ is the number of corrective interventions, $n_{ops_{prev}}$ is the number of preventive interventions and $n_{devices}$ the number of devices in the ORE farm.

- *Combination of access systems*: in the characterisation tool, having a combinations of access systems available means that when a maintenance task is required, the model checks all the access systems which have sufficient capabilities to perform the specific intervention and the cheapest vessel among those available (lowest sum of standby rate, daily rate and mobilisation cost) is selected. This means that if two selected access systems are somehow complementary in capabilities there will be an increase in availability of the farm, therefore in generated revenue, which usually highly compensates the expenses of considering (therefore renting or purchasing) two or more access systems in the same fleet. Hence, when two or more different kinds of vessels are considered in the maintenance fleet, there should be an indirect decrease of the cost function. On the other hand, if the considered access systems are very similar, these advantages will not be as significant as in the previous case or the case in which only one of the access systems is considered for the O&M of the farm. In other words, solutions in which two or more access systems are considered in a mixed maintenance fleet are favoured because their complementary capabilities will result in a decrease in the lost production and repair costs (e.g. by using quicker and cheaper workboats for minor interventions and bigger vessels exclusively for medium or major interventions).

Consequently, the factor that most contributes to a decrease of the cost function is the relative difference in capabilities between the access systems considered. The difference in price (intended as sum of standby rate, daily rate and mobilisation cost), is often a direct consequence of considering access systems with very different capabilities. For instance small crew transfer vessels (CTVs), with very limited capabilities and mostly suitable for minor maintenance tasks, are always cheaper than bigger and more capable vessels or multicat boats. An exception is often given by helicopters, that due to their higher accessibility and operability in harsher conditions, are often more expensive than small boats even if with similar maintenance capabilities.

In the chromosome, the combination of access systems is not explicitly stated; however it is considered as allowed when two or more kinds of access system, with at least one unit, are considered. Taking advantage of the frequent price difference (daily, standby and mobilisation rates) between different access systems, a factor contributing to decrease the cost function, proportional to the price difference between access systems and to the cost of the most expensive access system, is considered as follows.

If n (more than one) access systems are considered in the chromosome, in order to consider *all* the mutual price ratios without repetition (e.g. $C_{A.S._2}/C_{A.S._3}$ but not $C_{A.S._3}/C_{A.S._2}$), the contribution to the cost objective function due to the combination of vessels is given by:

$$C_{COMB} = -\left(\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \frac{2(C_{A.S._i}/C_{A.S._j})}{n(n-1)} \right) \cdot C_{A.S._{MAX}} \tag{3.9}$$

if the combination is allowed, otherwise this term is null. As stated above, this contribution takes this form because a non repetitive sum over the cost ratios of all vessels is pursued as a mean of quantifying the difference in capabilities among access systems. In order to aid clarity and provide further details, the algorithm for this contribution to the cost function is reported in Algorithm 3.1.

Algorithm 3.1: Calculation of C_{COMB}

```
l=[i for i in xrange(len(C_as_comb_use))] # list created to start internal loop from 1 rather than 0
C_as_ratio=[]
for i in xrange(len(C_as_comb_use)-1): # external summation in formula
 for j in l[1:]: # internal summation in formula
  if i!=j and (i,j != j,i): # to avoid considering a.s. with the same indexes
  r = C_as_comb_use[i]/C_as_comb_use[j]
   if r<1: # in order to avoid considering the ratio twice (e.g. a.s.1/a.s.2 and a.s.2/a.s.1)
    C_as_ratio.append(r)
C_as_ratio_avg=sum(C_as_ratio)/len(C_as_ratio)
C_comb = -(C_as_ratio_avg)*max(C_as*(numpy.array(accsys_units)>0))
```

- *Number of units per access system*: In the Monte Carlo tool the number of units of a certain access system available in the fleet is used to introduce limitations on the total time required for a maintenance task. Each maintenance operation starts as soon as a failure is detected or the time for a planned operation comes, but only if an access system is available at that moment. This means that if there are more corrective or preventive maintenance tasks than available access systems, the operation will be delayed until when one of the access systems has completed a previous task and is available again. Therefore, the more units available, the lower the risk of introducing delays in the maintenance of the farm, thus indirect reduction in cost due to reduced production losses. On the other hand, the expenses to hire or purchase an increased number of units will be higher. Therefore a balance is required in the ratio between the number of units and the number of maintenance interventions (both planned and unplanned).

Under these considerations, the contribution of the number of units for each access system considered to the cost objective function is modelled as:

$$C_{UNITS} = |k_{units} - c_{units}| \cdot C_{A.S.} \cdot \; k_{n_{years}} \tag{3.10}$$

where:

$$k_{units} = \frac{n_{units}}{n_{int_{prop}}} \tag{3.11}$$

is the ratio between the number of units of an access system and its estimated number of maintenance interventions; and

$$c_{units} = k_{units_{ideal}} = \frac{n_{units_{ideal}}}{n_{int}} \tag{3.12}$$

is the ideal ratio, according to the results of the characterisation model and engineering considerations, between the number of units and the number of interventions for each access system.

In turn,

$$n_{int_{prop}} = use_{a.s} \cdot n_{int} \tag{3.13}$$

is the number of interventions proportionally to each vessels usage ($use_{a.s}$, in percentage, estimated with the characterisation tool); and n_{int} is the number of planned and unplanned maintenance interventions per year estimated with the characterisation tool introduced above.

$k_{n_{years}}$ is an optional multiplicative factor introduced to eventually account for the difference between the number of interventions per year and those for simulated lifetimes of longer periods. It can be used to adjust the ideal ratio between number of units and number of interventions depending on the simulated lifecycle of the ORE farm, as well as to account that longer lifetimes may not scale linearly from the per year values.

- *Overnight operability of the access systems*: if a vessel is able to perform maintenance interventions overnight there will be a reduction of the lost production as a consequence of a higher capacity of restoring the functionality of the device in case of failures. At the same time, an increase in direct O&M cost has to be expected due to higher wages for the maintenance staff and other expenses (e.g. port fees) for the night shifts.

  As a consequence, two contributions to the cost objective functions are included. The first takes into account the indirect decrease in costs as a result of a higher availability of the vessel. This is usually related to the significance of the component to repair, which in turn is related to the capabilities of the vessels, and therefore modelled as proportional to the cost of the access system previously given by Equations (3.6) and (3.7) and a constant $c_{OV_{IND}}$:

$$C_{OVERNIGHT_{INDIRECT}} = \sum_{i=1}^{n_{A.S.}} -c_{OV_{IND\,i}} \cdot C_{A.S._i} \tag{3.14}$$

  Indicative values of the multiplicative factor $c_{OV_{IND\,i}}$ can be assessed using the characterisation tool, with values usually in the range 0.15-0.30. The second variation of the cost function related to the possibility of having access systems operating overnight is a direct increase in costs as a result of the increased crew salary for overnight operations, and is modelled as:

$$C_{OVERNIGHT_{DIRECT}} = \sum_{i=1}^{n_{A.S.}} c_{OV_{D\,i}} \cdot Crew\ cost_i \tag{3.15}$$

  Indicative values of the multiplicative factor $c_{OV_{D\,i}}$ can be directly related to the variation in crew costs (e.g. additional costs derived from the fact that staff operating overnight will require higher compensations), therefore given by the ratio between crew costs with compensation for overnight operations and ordinary crew costs for diurnal operations only, for instance:

$$c_{OV_{D\,i}} = \frac{Crew\ cost_{OVERNIGHT-NO}}{Crew\ cost_{OVERNIGHT-YES}} \tag{3.16}$$

However, the ideal is to adjust the values of both $c_{OV_{IND_i}}$ and $c_{OV_{D_i}}$ according to eventual engineering considerations and especially feedback obtained from the outcomes of the characterisation model for different case studies, as shown in Section 4.2.

- *Limited availability of the access systems*: a limited availability of the vessels, for instance during the summer months or when the vessels are chartered elsewhere, will increase the costs due to production losses. On the other hand, not only there will be fewer interventions and therefore less expenses due to mobilisation of the vessels and maintenance of the devices, but also the related port and maintenance fees, as well as staff costs and eventual hire expenses, will decrease. Therefore, similar to the previous point concerned with the contribution of the overnight operability of the vessels, both a direct increase and an indirect decrease of the cost objective function are modelled to take into account eventual seasonality restrictions of an access system. The first factor is an indirect reduction of the cost function as a consequence of a minor use of each access system if there are restrictions on its availability:

$$C_{SEASONALITY_{INDIRECT}} = \sum_{i=1}^{n_{A.S.}} -c_{SEAS_{IND_i}} \cdot C_{A.S._i} \tag{3.17}$$

The second factor is a direct increase of the cost function. This cost increase is inversely proportional to the restriction, and therefore proportional to the actual availability (in terms of number of months over a year) of the vessel, in order to take into account that, if the vessel is purchased, the more it has to be available for eventual interventions the more it will cost to keep it operational (crew, port and maintenance fees):

$$C_{SEASONALITY_{DIRECT}} = \sum_{i=1}^{n_{A.S.}} \frac{n_{months_{AVAILABLE_i}}}{12} \cdot Standby\ rate_i \tag{3.18}$$

It should be remembered that in the characterisation model the standby rate was used to represent the expenses related to keep the vessel ready to work in port if this was a property of the farm, and might be set to 0 if the vessel was rented. As a consequence, this second factor applies only if the vessel is purchased.

Similarly to the coefficient for the overnight operations, in order to find a suitable value for the constant $c_{SEAS_{IND i}}$ a first option consists in using a similar criterion used for the direct variations (e.g. the ratio between the months the vessel is actually available and the number of months per year), but again a better alternative consists in calibrating its value using the characterisation tool as a reference, as shown in Section 4.2.

- *Redundancy of the components*: given the engineering restrictions in the design of the device, the eventual introduction of redundant components will impact the cost both directly and indirectly. The direct costs are incurred due to the associated costs of purchasing and installing the redundant elements, while the indirect decrease in cost is incurred as a consequence of the increased reliability of the device. Thus, the direct increase in the cost objective function is calculated as:

$$C_{RED_{DIRECT}} = \sum_{i=1}^{n_{comp.}} \left(n_{red_i} \cdot \Delta c_{red_i}\right) \cdot red_i \tag{3.19}$$

where n_{red_i} is the number of redundant elements introduced for the component i, Δc_{red_i} is the additional cost of the installation of each redundant element for the considered component, and red_i is the number of components to which redundant elements are applied.

In order to take into account the indirect decrease of the cost function as a consequence of the installation of redundant elements, the relative increase in both the reliability and availability of the device, calculated as detailed in the description of the corresponding objective functions in the next sections, is considered. Therefore this contribution becomes:

$$C_{RED_{INDIRECT}} = -C_{A.S._{tot}} \cdot \left(\Delta Av_{RED}\,(\%) + \frac{\sum_{i=n_{comp.}} red_i}{n_{comp}} + \frac{REL}{REL_{IDEAL}}\right) \tag{3.20}$$

where $\Delta Av_{RED}\%$ is the percentage increase in availability as a result of the introduction of redundant elements, red_i is the number of components for which redundant elements have been introduced, n_{comp} the total number of components in the device, REL the reliability calculated after the introduction of redundant elements and REL_{IDEAL} the ideal reliability of the device with all the possible improvements applied. $C_{A.S._{tot}}$ is the sum of all the cost entries relative to the access systems cost (but not those related to reliability improvements on the device) introduced so far, hence given by:

$$C_{A.S._{tot}} = C_{A.S.} + C_{COMB} + C_{OVERNIGHT_{DIRECT}} + C_{OVERNIGHT_{INDIRECT}} + \\ + C_{SEASONALITY_{DIRECT}} + C_{SEASONALITY_{INDIRECT}} + C_{UNITS} \quad (3.21)$$

- *Failure rate reduction of the components*: in the same way as to the previous contribution, if available, better or more reliable components (i.e. with lower failure rates) will be more expensive to purchase and replace in case of failure, causing a direct increase in the cost function. On the other hand, their replacement will be less frequent, making the device more reliable and thus decreasing the costs by reducing the number of maintenance interventions. The direct increase to the cost function is thus calculated as:

$$C_{FRR_{DIRECT}} = \sum_{i=1}^{n_{comp.}} \Delta c_{frr_i} \cdot frr_i \quad (3.22)$$

where Δc_{frr_i} is the additional cost of having a more reliable version of the same component and frr_i is the number of components for which more reliable products are chosen. Similar to the previous contribution, the relative increase in both the reliability and availability of the device is used in order to take into account the indirect decrease of the cost function as a consequence of the selection of more reliable components:

$$C_{FRR_{INDIRECT}} = -C_{A.S._{tot}} \cdot \left(\Delta Av_{FRR}\,(\%) + \frac{\sum_{i=n_{comp.}} frr_i}{n_{comp}} + \frac{REL}{REL_{IDEAL}} \right) \quad (3.23)$$

where $C_{A.S.tot}$ is the total cost of access system for the considered individual and $\Delta Av_{FRR}(\%)$ is the variation in availability with respect to the case of the same individual with no redundant elements for all the components.

- *Overnight operability of the components*: likewise the overnight capability of the access systems, having components that can be maintained overnight reduces downtime and production losses (resulting in an indirect cost decrease). The overnight operability of the components therefore also has both direct and indirect costs associated with it. At the same time, similar to what is observed for higher quality or more reliable components, additional expenses, may be incurred to acquire components that can be repaired or replaced at any time (including overnight).

$$C_{OVERNIGHT_{COMP_{DIRECT}}} = \sum_{i=1}^{n_{comp.}} \Delta c_{ov_i} \cdot ov_i \tag{3.24}$$

where Δc_{ov_i} is the marginal cost associated with a component's ability to be operable overnight and ov_i is the number of components for which products operable also overnight are chosen.

In order to take into account the indirect decrease of the cost function as a consequence of increased repairability of the device overnight, the relative increase in availability is considered, and the contribution is modelled as:

$$C_{OVERNIGHT_{COMP_{INDIRECT}}} = -C_{A.S.tot} \cdot \Delta Av_{OV}(\%) \tag{3.25}$$

where $C_{A.S.tot}$ is the total cost of access system for the considered individual and ΔAv_{OV} is the variation in availability with respect to the case of the same individual with 0 overnight repairable components.

- *Immediate spare parts availability of the components*: having spare parts for a certain component always available means that, in the event of a failure, eventual procurement times for that component are null, reducing repair times hence production losses. This comes at a cost, for instance due to higher investments in the spares and the need of bigger warehouse/engineering team to store/manage them. Therefore, similar to the previous contribution for overnight operability of the components, a direct contribution representing the additional costs in order to have immediate availability of spare parts is modelled as:

$$C_{SPARES_{DIRECT}} = \sum_{j} \Delta c_{spares_i} \cdot spares_i \tag{3.26}$$

where Δc_{spares_i} is the additional cost of having immediate availability of spare parts for the component i and $spares_i$ is the bit of the chromosome stating whether this improvement is considered or not for the same component. Again, in order to take into account the indirect decrease of the cost function as a consequence of having immediate availability of spare parts, the relative increase in availability is considered:

$$C_{SPARES_{INDIRECT}} = -C_{A.S._{tot}} \cdot \Delta Av_{SPARES}(\%) \tag{3.27}$$

All the direct component-related contributions to the cost function (redundancy, failure rate reductions, immediate availability of spare parts, overnight operability) are multiplied by the total number of devices in the ORE farm for the calculation of the cost objective function.

3.2.2.2 Reliability objective function

The second objective function considered to evaluate the fitness of each solution with respect to the others is the reliability function. This is dependent only on the taxonomy of the device and the configuration of its sub-assemblies. As such, the reliability of the devices is computed starting from the values of the individual components' failure rates, taking into account the placement of the components in series or in parallel systems, as well as eventual redundant items and the minimum number of these (*k-out-of-n*) which are needed for the device to remain operational. These equations, described in Section 2.3.1, are the same used to calculate the reliability in the characterisation tool, and therefore no calibration nor benchmarking with their implementation in the optimisation tool is needed.

3.2.2.3 Availability objective function

The third and last objective function considered in the surrogate model is the availability. As this is usually measured as a percentage, where 0% corresponds to no energy production due to continuous downtime and 100% to the production in the ideal scenario of null downtime, the contributions to the objective function A_i are calculated in such a way that in an ideal situation all the contributions would sum up to 100, i.e. $\Sigma_i \; A_i <= 100$. The values for each decision variable (or set of these) are then assigned proportionally to the relative importance of the contribution, previously calibrated through comparison with the characterisation tool, as shown in Section 4.2.2. The availability ranges, divided by contribution, are assigned as follows:

- Number of access systems units: Range 0-25;
- Continuous availability of the access systems (no seasonality restrictions): Range 0-25;
- Immediate availability of spare parts: Range 0-20;
- Overnight repairability of components: Range 0-10;
- Redundancy of components: Range 0-10; and
- Failure rate reductions: Range 0-10.

Hence, the same consideration made for the calculation of the cost objective functions on both the maintenance access systems and device components, can be used to calculate the scores in the availability objective function. However, unlike the cost objective function, the variables with respect to the availability have no direct drawbacks (e.g. additional costs due to capital expenditures). For example, the higher the number of access systems, or the more reliability related improvements, the higher the availability will be. The formulation of these contributions are detailed below.

- *Number of units per access system*: With respect to only the availability, the more units of access systems in the fleet the better, because this assures a higher possibility of having a vessel available whenever needed for maintenance interventions. Therefore, it is possible to assign the maximum score of this entry range (i.e.

25) when the maximum number of access systems in the fleet is considered, and proportional quantities of this score when only a fraction of the maximum number of units is considered. An upper boundary for the number of units is given by the sum of the maximum number of units expressible with the chromosome, pre-established according to the number of digits used to specify the number of units of each access system. This value follows the relationship described in the previous section (max units representable = $2^{n_{BITS}} - 1$). Therefore, for $n_{A.S.}$ kinds of access systems, the total number of units in the fleet is:

$$Fleet_{MAX} = n_{A.S.} \cdot 2^{n\ bits-1} \tag{3.28}$$

In addition, the benefits of a combination of vessels are considered by introducing a multiplicative factor which takes into account if the combination is allowed or not. In this way the score for the availability related to the number of access systems is:

$$Av_{UNITS} = \frac{\sum_{i=1}^{n_{A.S.}} A.S._{units}}{Fleet_{MAX}} \cdot (score_{units} - n_{A.S.}) + n_{A.S.} \cdot COMB \tag{3.29}$$

where $score_{units}$ is the maximum score for this contribution as established in the range (i.e. 25), $Fleet_{MAX}$ is the maximum number of access systems in the fleet. This means that if the combination of access systems is not allowed ($COMB = 0$) the maximum score obtainable is reduced by an amount equal to the kinds of access systems considered in the possible fleet (n). Conversely, if the combination is allowed ($COMB = 1$), a sort of "bonus" score equal to the number of different kinds of a.s. considered is assigned to this score. For example, if three access systems are available but only one considered in a particular individual, the maximum value this contribution can assume is 22 (because the maximum score is 25 and $n_{A.S.} \cdot COMB$ would give 3).

- *Limited availability of the access systems (seasonality restrictions)*: as already mentioned, the more available the vessels the higher availability of the ORE farm as a consequence of more immediate maintenance interventions. Thus this contribution is modelled as:

$$Av_{SEASONALITY} = \frac{\sum_{i=1}^{n_{A.S.}} A.S._{always\ available_i}}{tot_{A.S.}} \cdot score_{seasonality} \tag{3.30}$$

where $score_{seasonality}$ is the maximum score for this contribution as established in the range, $tot_{A.S.}$ is the total number of access systems in the fleet.

- *Redundancy of the components*: by taking advantage of the relationships used to calculate the reliability of a system, the availability value associated to the introduction of redundant items for certain components can be quantified as being proportional to the marginal increase in reliability achieved as a consequence of the redundancy measures. Under this assumption the increment in availability is given by:

$$Av_{RED} = \sum_{i=1}^{n_{comp.}} red_i \cdot score_{red_i} \tag{3.31}$$

where red_i is the digit corresponding to the redundancy measure of each component and

$$score_{red_i} = \frac{score_{red} \cdot R_{redi}}{\sum_i R_{redi}} \tag{3.32}$$

where $score_{red}$ is the maximum score of the range related to redundancy improvements (i.e. 10), and R_{redi}, previously calculated for the reliability objective function, is the individual contribution of each branch (configuration of redundant elements) to the reliability of the system as a consequence of redundancy measures. It accounts also for the number of redundant items introduced for each component.

If for a component redundant elements cannot be added, these will not be considered for a positive score in the availability function calculation (in order to respect the engineering constraints).

- *Failure rate reduction of the components*: Lower failure rates are indisputably preferable to achieve higher availability. These can be achieved as a consequence of improvements in the design of the individual component, or the choice of a better (more reliable) version of the same component. These improvements have repercussions on the reliability and cost of the offshore farm, but also on its availability. Considering a number of components of the device n_{comp} (and the same number of corresponding digits in the chromosome), the availability value related to using components with lower failure rates can be quantified as:

$$Av_{FRR} = \sum_{i=1}^{n_{comp.}} frr_i \cdot score_{frr_i} \tag{3.33}$$

Where frr_i is the digit corresponding to the failure rate reduction of each component and the maximum score assignable to the contribution to availability for the failure rate reduction $score_{frr}$ is given by:

$$score_{frr_i} = \frac{score_{frr} \cdot \Delta\lambda_i}{\sum_i \Delta\lambda_i} \tag{3.34}$$

where $\Delta\lambda_i$ is the decrease in failure rate for the i_{th} component. In other words, the sum of all the possible availability contributions must be equal to the proposed total score for this decision variable, i.e. 10:

$$\sum_{i=1}^{n_{comp.}} \frac{score_{frr} \cdot \Delta\lambda_i}{\sum_i \Delta\lambda_i} = score_{frr} = 10 \tag{3.35}$$

Therefore each component's failure rate reduction contributes to the availability value proportionally to the decrease in its failure rate, and, if applied, the sum of all contributions gives $score_{frr}$. Concern may arise due to the fact that the availability increase corresponds only to a quantitative factor related to the failure rate of the component, but independent on the nature of the considered component. This means that higher failure rate reductions in relatively less important or easy to repair components may produce a higher increase in availability with respect to lower failure rate reductions on very important or difficult to repair components. Nonetheless, increases in availability exclusively proportional to reductions in failure rates shall be considered for this entry due to the difficulty in including qualitative aspects on this class of improvements.

If the failure rate reduction is null, meaning that improvements are not possible for that specific component, these components will not contribute to the increase of the availability function. This is a necessary assumption in order to compare solutions that provide an increment in availability as a consequence of some action or choice (decision variable).

- *Overnight repairability of the components*: analogous considerations to the previous case of failure rate reduction, and their link to the chromosome structure and the availability function, can be made with reference to the overnight repairability of the components. As a consequence, the availability value related to this potential improvement can be quantified as:

$$Av_{OV} = \sum_{i=n_{comp.}} ov_i \cdot score_{ov_i} \tag{3.36}$$

where ov_i is the digit corresponding to the overnight reparability of each component (1= yes, 0= no) and the score assignable to the contribution to availability for the overnight repairability of the components $score_{ov}$ is given by:

$$score_{ov_i} = \frac{score_{ov} \cdot \Delta p_i}{\sum_i \Delta p_i} \tag{3.37}$$

where Δp_i is the increment in probability that the system will be restored to its operable condition in a specified repair time due to the increase in reparability. Again, if a component, for any reason, cannot be repaired overnight and as a result its $\Delta p_i = 0$, then it will not be considered for a positive score in the availability function calculation for the same reasons stated above (i.e. it is necessary to distinguish between those solutions that ameliorate the systems and those which do not).

- *Immediate spare parts availability of the components*: the last contribution to the availability objective function is related to the immediate availability of a spare part in case of failure of a component. Having a spare part always available, or procurable in a short time, means quicker repair operations and higher availabilities of the farm. On the contrary, the lack of a spare part in stock means the addition of a procurement time to the downtime of the farm, with consequent delays in maintenance interventions and reduction of the availability. Hence, higher values of the availability function shall be obtained if for a certain component there is always at least a spare part available or immediately procurable in case of need for replacement. Therefore this contribution can be formulated as:

$$Av_{SP} = \sum_{i=1}^{n_{comp.}} \frac{SP_i \cdot score_{SP}}{n_{comp}} \tag{3.38}$$

where SP_i is the digit corresponding to the spare part immediate availability of each component (1= yes, 0= no), $score_{SP}$ the availability range associated to this contribution and n_{comp} the total number of components in the system.

3.2.2.4 Other contributions

Besides these considerations and correspondent contributions on the calculation of the respective objective functions, penalties are introduced to take into account the limitations and difficulties in establishing the most suitable value for a number of different conditions, thus the value for the decision variables of the considered problem. Even though in optimisation vernacular penalties are commonly used to handle constraints, in this work these are used to ensure that the impact of interactions between decision variables are captured in the objective functions.

Consequently, a penalty in the calculation of the cost function is introduced after considering the correlation between components maintenance categories and access systems maintenance categories (maintenance categories, described in Section 3.1.2.1, are used to classify the extent of an intervention (e.g. minor repair, major replacement, etc.). This reduces the probability of favouring possibly undesired solutions (e.g. with numerous units of expensive access systems that can be used only for a limited number of major repairs).

However, rather than assigning a score depending on the level of correlation, a penalty function (i.e. a negative score) is assigned proportionally to the lack of correlation. This, reflects also the uncertainty and difficulty in establishing the proper number of access systems. The measure of how effective a correlation is, has been formulated on the following intuitive considerations and supported by the results of the calibration and benchmarking with the characterisation model shown in Section 4.2.2:

- the more components an access system can operate on, the more units of that access system are desired;
- the higher the failure rate of those components that an access system can operate on, the more units of that access system are desired; and
- the higher the cost of renting/purchasing an access system, the less units of that access system are desired.

Therefore the penalty function depends on: the number of units of the access system in relation to the number of components that can be repaired with that access systems, the failure rates of these components and the cost of the access system itself.

Furthermore, in the characterisation model, when a higher number of units are selected but these are not a property of the farm, there is not a significant variation in the O&M cost. This is due to the way the vessels costs are computed, which is according to their use; the cost of a vessel is directly proportional to the number of times the vessel is mobilised and the duration of the task it is involved in. As a consequence, for an effective benchmarking of the two computational models, the cost penalty related to the number of units of an access system in the GA is considered only if the vessel has been purchased, i.e. the ownership for that access system is set to 1.

Under these circumstances, the penalty function assumes the form:

$$C_{PENALTY} = \sum_{i=1}^{n_{A.S.}} \frac{standby\ rate_{A.S.}}{\frac{n_{comp_{A.S.}}}{n_{comp_{tot}}} \cdot \frac{\sum_{i=n_{comp_{A.S.}}} \lambda_i}{\lambda_{tot}}} \cdot \frac{A.S._{units}}{max_{units}} \cdot ownership_{A.S.} \tag{3.39}$$

where $n_{comp_{A.S.}}$ is the number of components on which the considered access system can operate (for which there is a match component-access system maintenance category), λ_i is the failure rate of each of these components, λ_{tot} is the sum of the failure rates of all the components, $standby\ rate_{A.S.}$ is the access system standby rate, $A.S._{units}$ is the number of units considered in the individual for that access system, $ncomp_{tot}$ is the total number of components in the device, max_{units} is the maximum number of units per access system given the number of digits allowed, and $ownership_{A.S.}$ indicates whether the access system is a property of the farm or not.

The algorithm for this contribution to the cost function is reported in Algorithm 3.2.

Algorithm 3.2: Calculation of C_{UNITS}

```
# Cost penalty due to uncertainty on number of units
C_penalty_units = []
for i in xrange(accsys):
C_penalty_prov = (standby_rate[i]*(accsys_units[i]/max_units))
    /((n_comp_as[i]/n_comps)*(lambda_cum[i]/lambda_tot))
C_penalty_units.append(C_penalty_prov)

C_penalty_tot = sum(numpy.multiply(C_penalty_units, individual
    [accsys*units_bits:accsys*units_bits+accsys])) # penalty
    considered only if ownership a.s. = 1
```

Similarly, a further penalty in the cost function is possibly introduced to account for the indirect variations in cost due to variations in reliability. In other words, since a more reliable device requires less maintenance interventions and decreases the direct O&M costs, solutions with a value of reliability far from the ideal situation with all the possible reliability related improvements in place (e.g. failure rate reductions and redundancy of the components) will be penalized. Therefore, this is a reliability related indirect cost variation, as opposed to the reliability related direct cost variations previously introduced and representing the possible increase of the cost function as a consequence of the introduction of more reliable or redundant elements. In order to give a penalty that is proportional to how far the reliability is from the ideal situation, this cost contribution is modelled as:

$$C_{RELIABILITY_{IND}} = \left(\frac{REL_{IDEAL}}{REL}\right) \cdot C_{A.S._{tot}} \tag{3.40}$$

Furthermore, the same constraints listed above for the creation of a chromosome, also apply at each step of the GA (any time that individuals are generated, crossed over and mutated) for the purpose of maintaining feasible solutions that either provide realistic solutions and satisfy the technical implications of the ORE farm management. In addition, eventual improvements can be limited with the inputs parameters, e.g. by setting a 0 in the number of redundant elements as a consequence of redundancy improvements if this possibility is not feasible due to constraints of the design of the device.

The constraints applied at each step of the GA are the same applied for the initial seeding of the chromosome, here reported for convenience:

- at least one unit of at least one access system in the maintenance fleet;
- not considering the properties of a vessel in the final solution if the vessel is not included in the fleet; and
- not assuming redundancy improvements if the pre-established possible number of redundant elements for a certain component is set to 0 due to technical requirements.

3.2.2.5 Summary

Unlike in characterisation models, the scores provided in the present optimisation model are relative measures, to be treated as a unitless comparison metric to evaluate the relative quality of solutions rather than to interpret them as an absolute estimate of the performance indicator for that parameter. In fact, for the purposes of the optimisation, all solutions have to be compared to one another. As a consequence, the maximum achievable accuracy in computing the true values with regards to the KPIs, wanted in the characterisation model, is not sought. This consideration is further discussed in Section 5.3.

Several of the variations in the contributions to the objective functions presented above are proportional, because of the simplicity, effectivity and flexibility provided in scaling the differences between different quantities as well as in discerning among different solutions. Despite other kinds of proportionality (e.g. exponential or logarithmic) may have been considered, the benchmarking process introduced in Section 4.2 has allowed for this choice to be kept.

A qualitative summary of the impact of each decision variable on the three objective functions is provided in Table 3.1. Here it can be seen how for all the decision variables, an increase in their value causes both a direct and indirect variation of the cost function and a direct increase of the reliability function. Regarding the availability function, depending on the decision variable considered, an increase in the value of the decision variable may correspond to either an increase or decrease of the objective function.

Table 3.1: Effect of the increase of each decision variable on the objective functions.

Decision variable	**Cost**	**Reliability**	**Availability**
Number of access system units	$\Uparrow$, $\downarrow$	-	$\uparrow$
Overnight operability of the access systems	$\Uparrow$, $\downarrow$	-	$\uparrow$
Ownership of the access systems	$\Uparrow$, $\downarrow$	-	$\uparrow$
Seasonality restrictions of the access systems	$\uparrow$, $\Downarrow$	-	$\downarrow$
Redundancy measures on device components	$\Uparrow$, $\downarrow$	$\Uparrow$	$\Uparrow$
Failure rate reduction of device components	$\Uparrow$, $\downarrow$	$\Uparrow$	$\Uparrow$
Overnight repairability of device components	$\Uparrow$, $\downarrow$	$\Uparrow$	$\Uparrow$
Immediate spares availability of device components	$\Uparrow$, $\downarrow$	$\Uparrow$	$\uparrow$

Legend: $\Uparrow$ = Direct increase, $\Downarrow$ = Direct decrease, $\uparrow$ = Indirect increase, $\downarrow$ = Indirect decrease, - = No variation.

3.2.3 Genetic algorithm approaches

In order to take into account the requirements and technical implications in selecting the most appropriate combination of assets for an OWF, multiple criteria must be considered. In fact, in order to increase the longevity and profitability of a project, the direct O&M costs deriving from the choice of the maintenance systems and possible interventions on the devices have to be kept as low as possible, while satisfactory levels of reliability are met and the availability of the devices is as high as possible in order to reduce the lost production due to downtime. Mere minimisation of the costs in a single objective optimisation would be reductive of the problem because very low values of reliability or availability may be achieved, deviating from the objectives discussed in Section 2.1.1 of finding a trade-off between cost reduction and increased production. Besides, according to the results of the benchmarking with the characterisation model presented in Section 4.2, the indirect contributions to the overall costs due to improvements in reliability or availability of the devices must be taken into account in order to effectively interpret possible variations in the assets management. As a result, the problem becomes a multi-objective optimisation aimed at minimising the costs while maximising both the reliability and the availability. Several multi-objective strategies using a GA exist (Konak *et al.*, 2006), and to explore their suitability for offshore O&M problems, three are implemented and compared in this work. These are hereinafter referred to as: 1) *Superposition method*, 2) *Weighted sum method* and 3) *VEGA inspired method*.

The first approach is called in this way because it superposes the results obtained by executing several single-objective optimisations for each of the individual objectives. In this, the individual objectives considered are:

- minimisation of costs;
- maximisation of reliability;
- maximisation of availability;
- minimisation of costs/reliability ratio; and
- minimisation of costs/availability ratio.

The GA framework illustrated in Figure 2.11 is applied separately for each one of these objectives. The selection process is based on the roulette wheel method (Deb, 2001). This is a common selection procedure based on assigning the individuals a probability of being chosen for crossover proportionally to their fitness value, as graphically exemplified in Figure 3.8. In other words, all fitness values are summed up and the contribution of each individual to the total sum determines its proportional probability of being selected.

A series of pros and cons exist in using this process (Fabritius, 2014). For instance, due to the fact that fitness values are perfectly reflected in the selection, the evolution advances rapidly towards the objective. However, the diversity, and consequent exploration of the search space, will rapidly decrease due to this convergence. Besides, if all fitness values are similar, the selection is almost as good as a random one.

Regarding the other GA mechanisms, a *single point crossover* is used; in this a "crossover point" is randomly selected, and bits from the beginning of the chromosome to the crossover point are copied from one parent while the remaining bits are copied from the second parent. Mutation occurs through the random inversion of a certain number of bits, proportional to the mutation rate. These steps are illustrated in Figure 3.9.

Exclusively for the superposition approach, two of the objectives represent the ratio between other objective functions. This is done in order to orientate the search in different areas of the investigated objective space, as illustrated in Figure 3.10 based on multiple runs of the implemented GAs. The results found with each single-objective

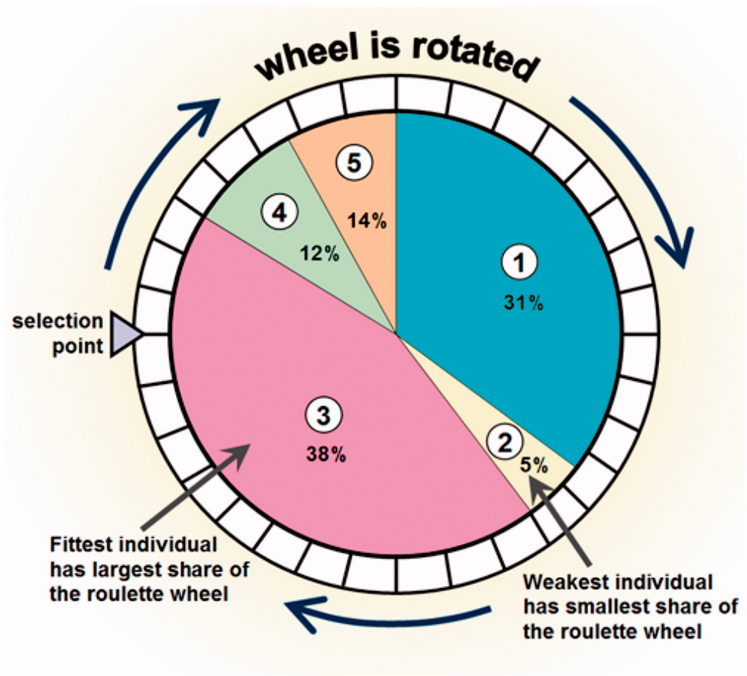

Figure 3.8: Example of roulette wheel selection based on fitness (Jun *et al.*, 2017).

optimisation, executed as described in Section 2.4.2, are then combined, and the Pareto frontier described in Section 2.4 is selected. In this way the directionality of the search towards different areas of the objective space is exploited, and average solutions with respect to all objectives which can potentially contribute to the definition of the Pareto front are kept. This process is illustrated in the flowchart in Figure 3.11; here, despite the individual single-objective optimisations are showed in series, there is no reason why these could not be run in parallel, i.e. the results of each single-objective optimisation are independent from those obtained with the others. The solutions lying on the Pareto frontier are considered as optimal in the wider sense that no other solutions in the search space are superior to them when all objectives are considered simultaneously (Zitzler & Thiele, 1999). In other words, as already mentioned, a solution belongs to the Pareto frontier if there is no way to further improve one objective without worsening at least one other. At this point it should be noticed that GAs are generally unable to guarantee that the Pareto front identified through the optimisation procedure is the true Pareto

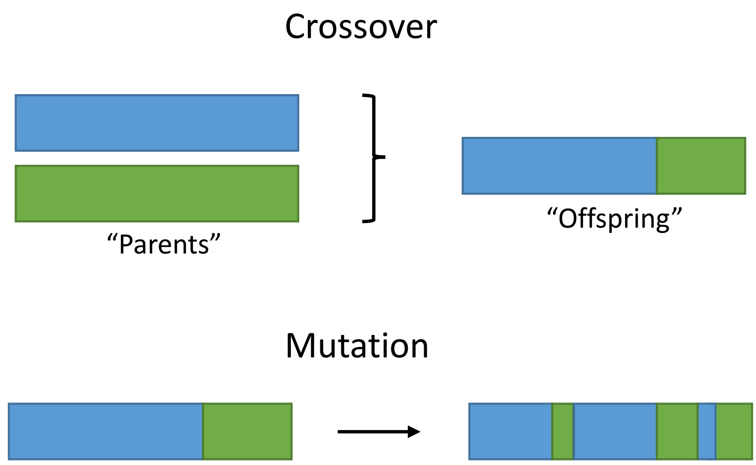

Figure 3.9: Graphical representation of the single point crossover and bit inversion mutation implemented in this work.

optimal for the investigated problem, but only that the set of best solutions are non-dominated (as defined in Section 2.4) with respect to all those identified during the search. For some specific problems, other techniques, e.g. linear programming, can be used to find the real Pareto optimal solutions and measure the distance from the non-dominated solutions found with the GA. However, for sake of simplicity, in this work the non-dominated front found with the GA will be referred to as Pareto front.

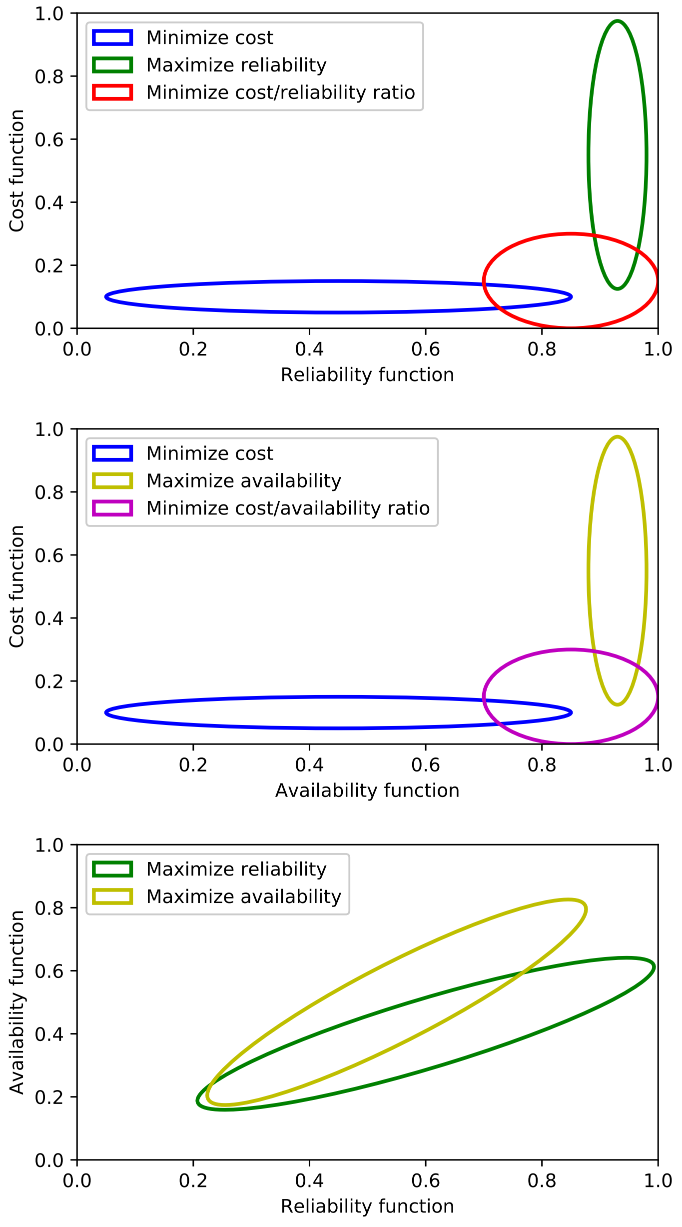

Figure 3.10: Example of areas of the objective space where the search for new solutions focuses depending on the objective function.

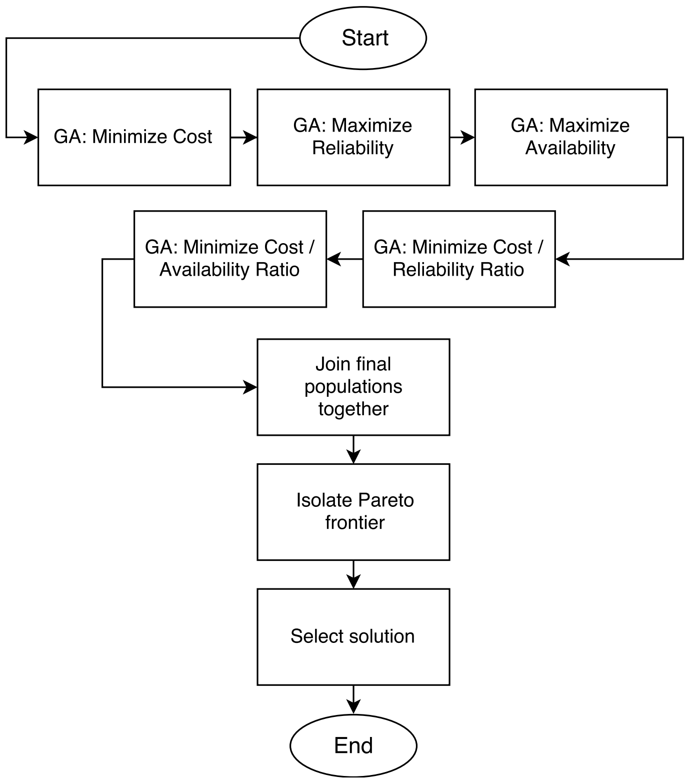

Figure 3.11: Flowchart of the approach exploiting individual single-objectives optimisations.

The second approach considered in this work is adapted from the *weighted sum method* (Marler & Arora, 2010). This consists in a linearisation of the problem by assigning a "weight" $\omega_i \in [0, 1]$ to each of the objective functions, such that $\Sigma_i\, \omega_i = 1$ and the linearised fitness of each solution is calculated by summing up the scores with respect to all the weighted objective values $\omega_i \cdot f_i(x)$. The principal challenge of using this approach is the selection of the appropriate weights for each objective function, since the value of each weight corresponds to the relative importance of the objectives. Similarly to the concept illustrated in Figure 3.10, each set of weights will orient the search towards a different region of the search space. Thus, in order to overcome this difficulty and to not favour explicitly one of the criteria (cost, reliability, availability) over the others, an iterative process in which the weights are changed randomly at each iteration is implemented. According to potential computational limits, a systematic sampling could be used in alternative. This process is depicted in the flowchart in Figure 3.12. Similarly to the other approaches, all the results obtained at each iteration are then combined in order to obtain the complete picture for the explored search space during all the iterations and the Pareto solutions selected. Another characteristic of this approach is that, once the problem is linearised by including all the objective functions and their weights in a single vector, only one objective is considered, i.e. either maximisation or minimisation of the resulting vector. Therefore the problem has to be rewritten in the following way:

maximise:

$$J(x) = w_c \cdot \frac{1}{f_c(x)} + w_r \cdot f_r(x) + w_a \cdot f_a(x) \tag{3.41}$$

where the reciprocal of $f_c(x)$ is considered because this individual term has to be minimised. This expression is subject to:

$$w_c, w_r, w_a \geq 0 \tag{3.42}$$

and

$$w_c + w_r + w_a = 1 \tag{3.43}$$

Where $f_c \equiv$ cost function, $f_r \equiv$ reliability function, $f_a \equiv$ availability function and the values of the objective functions are normalized in order to avoid any biases imposed by the different scales of the various objectives.

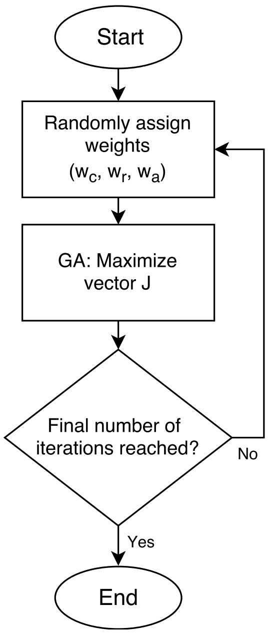

Figure 3.12: Flowchart of the approach exploiting the weighted sum method.

Finally, the third approach considered is inspired to the *Vector Evaluated Genetic Algorithm (VEGA)* (Schaffer, 1985), and its process is illustrated in the flowcharts in Figures 3.13 and 3.14. The VEGA approach was the first GAs developed for multi-objective optimisation. This exploits the subdivision of the population into sub-populations of relevant individuals, where a different objective is assigned to each sub-population, in order to emphasise solutions which are good with respect to one of the objectives (Circiu & Leon, 2010). In order to find intermediate solutions (compromise between different objectives), crossover is then allowed between two individuals, proportionally selected, belonging to any of the sub-populations.

In the approach implemented in this work, a different score, for each one of the objective functions, is assigned to each individual of the population. The initial population is then split into k sub-populations (where k is the number of objectives) by picking the best n/k individuals (where n is the size of the population) according to the results of each evaluation. A new population is then obtained by recombining these sub-populations and the GA can continue as usual, with crossover and mutation of selected individuals. Similar to the previous approaches, the objective functions considered in this work are the minimisation of the cost, the maximisation of the reliability and the maximisation of the availability. With respect to the ordinary VEGA, the selection mechanisms are slightly different in light of the computational results obtained, which demonstrated major capacity of exploration in different areas of the search spaces. In fact, the selection of the individuals for mating is carried out through two options. In the first variant, the two individuals ("parents") are randomly selected by picking one each from two of the three sub-populations obtained before these are shuffled together, whereas in the second variation a selection process based on the roulette wheel method described above is used after the three sub-populations are shuffled together.

In the same way as the previous approaches, the results of both variations are combined together to take advantage of the different areas of the search space explored. In this way, the extents of the search space are investigated, a quality desirable at the beginning of the search procedure before the search converges towards improved solutions, and the exclusive selection of individuals that excel in only one of the three objectives is avoided. As a consequence, also the selection of individuals which are moderately good with respect to all the objective functions, and thus may be useful to find compromise solutions, is ensured.

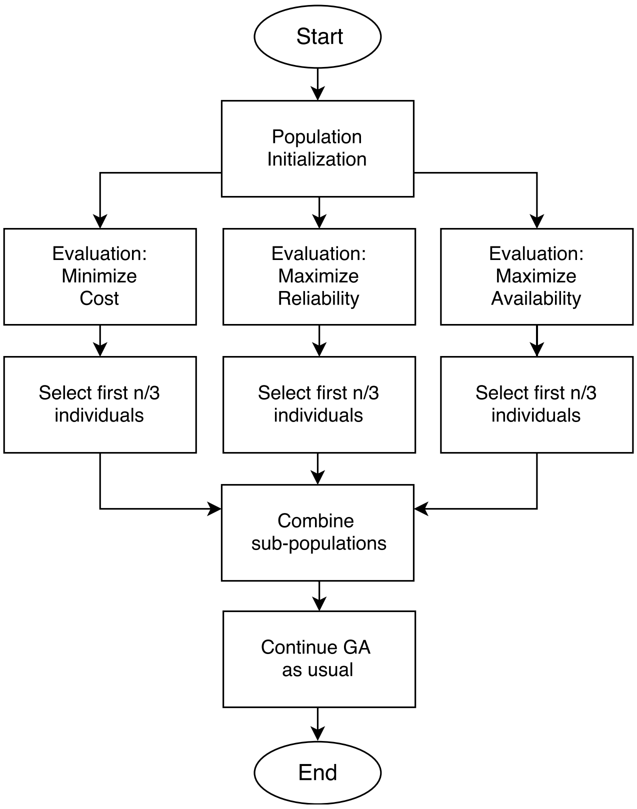

Figure 3.13: Flowchart of the approach inspired to the VEGA method, variant 1.

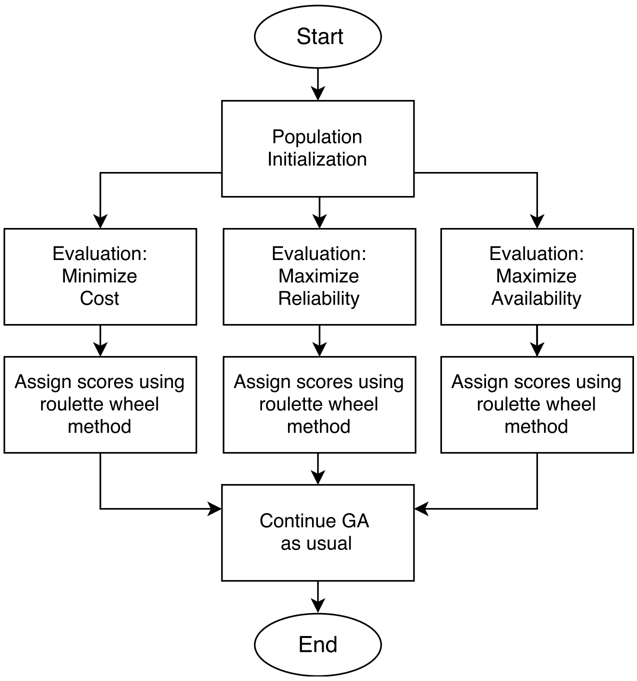

Figure 3.14: Flowchart of the approach inspired to the VEGA method, variant 2.

For all the three approaches, the parameters to control the execution of the GA are assigned according to indications given in the literature (Grefenstette, 1986) and then further tuned in order to achieve a good balance between extensiveness of the search and computational time. A series of preliminary tests based on a sensitivity analysis of the best and average fitness values has been used for this purpose, taking into account their absolute value and, since the two values should ideally converge, the relative difference between them. However, generally there is no optimal parameter configuration nor general search algorithm that works well for all problems. Nonetheless, the control parameters can be refined by looking at the solutions identified in the objective space. If these are too concentrated in the same area, crossover should be increased because this favours "big jumps" in the search space. Vice versa, if solutions are too spread, the mutation rate should be reduced because this parameter regulates local searches around each identified solution. If necessary, crossover and mutation rates can be left as variable and able to self-adapt depending on pre-established rules and feedback from each optimisation cycle, e.g. *crowd* parameters (number of solutions around a solution) (Maniu & Dumitru, 2017). In this way both the diversity in the population and the convergence of the GA towards optimal solutions are maintained (Srinivas & Patnaik, 1994). Similarly, the number of generations can be left as a function of the relative improvement between two consecutive Pareto fronts, and a maximum computational time or number of generations used as stopping criterion.

However, despite variable parameters can improve the quality of the search, GAs with fixed parameters are easier to implement and the results generated are generally equally valuable. The control parameters used in this work are given in Table 3.2.

Table 3.2: GA control parameters.

Parameter	**Value**
Generations	30
Population size	50
Elite individuals	5
Crossover rate	0.84
Mutation rate	0.01
Encoding	Binary

3.2.4 Outputs

In this section a description of the outputs achievable with the optimisation tool is provided. Figures based on multiple runs of the GAs for different cases, not related to any specific ORE farm, are presented in order to both test the validity of the implemented approaches and show the procedure to reach optimised O&M solutions.

To begin with, in order to confirm the effective functioning of the GA and eventually refine the GA parameters (e.g. number of generations, population size, crossover and mutation rates), a series of preliminary optimisation tests can be performed. Thus, initially only one objective is considered, i.e. the minimisation of the maintenance costs, and the evolution of the population, generation by generation, is evaluated. In order to track the improvement and convergence characteristics of the optimization routine, the best fitness value and the average fitness value of the population are monitored as shown in Figure 3.15. As would be expected, if it is a maximisation problem both values should increase as the number of generation increases, whereas if it is a minimisation problem (e.g. minimise costs) they should both decrease. Furthermore, if the optimal solution is being reached, the two trends of best and mean will converge as the number of generation increases, providing a feedback in order to establish the proper number of generations (tune the GA parameters) accordingly.

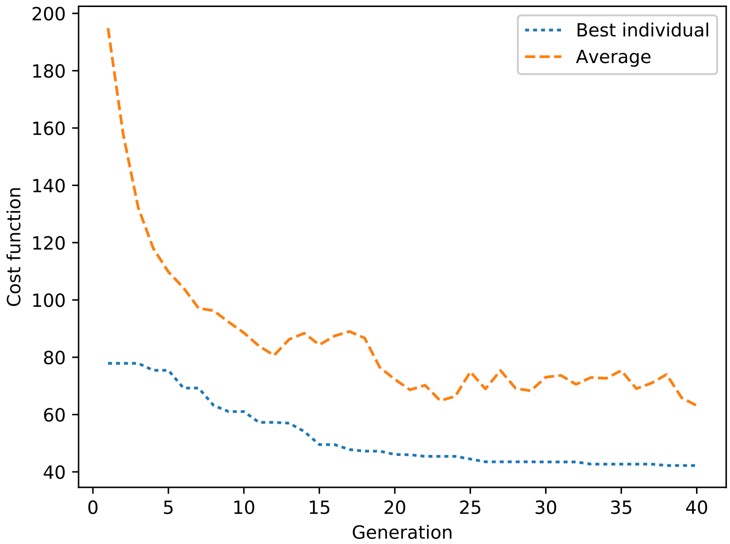

Figure 3.15: Example of trend of best and average individuals along generations for a minimisation problem (decrease cost function).

Another method to verify the effective validity of a GA as an optimisation approach is comparing the Pareto frontier obtained with the GA, described in Section 2.4, with that achievable through a random search with the same number of generations and individuals in the population. A random search is in effect a lower limit on acceptability for optimisation processes, but this test further supports the investigation on the correct implementation of the GA. The random individuals have to be generated satisfying the same feasibility constraints applied in the GA, but do not follow any evolution process that leads to optimisation. In this way, if the extents of the Pareto front obtained with the GA are larger (i.e. “more optimised” solution) than those obtained with the random search, despite it cannot be demonstrated that the true Pareto front constituted by the optimal solutions is always achieved, the additional value of GA as an optimisation method is demonstrated, as shown in Figure 3.16. Here, the spread of the random individuals indicates that the decision space is not uniformly mapped across the solution space, due to the higher density at the middle of the reliability range. On the other hand, the GA individuals tend to focus the search on those areas that are beneficial with respective to the set objectives, i.e. minimise cost and maximise reliability. This is further supported by the extension and position of the respective

Pareto fronts. As mentioned in Section 2.4, also the shape of the Pareto front advises on the effectiveness of the search and up to what point, or region, is worth pushing it (e.g. before the cost rises too steeply).

For a more complete overview on the performance of the GA, the optimised solutions and Pareto frontier could be compared against *all* the possible feasible solutions obtained through a full enumeration case. However this poses additional difficulties due to the large number of generated solution. For instance, according to the structure of the chromosome introduced in Section 3.2.1, with an individual accounting for 3 access systems and 8 components of the device, and including all the related properties as specified in the same section, 50 digits are needed to represent it, which gives a total of 2^{50} (1,125,899,906,842,624) possible individuals to take into account all the possible combinations (excluding feasibility constraints). The eventual generations of this number of individuals produces computational problems that suggest to return to a more manageable random generation of individuals and consequent comparison.

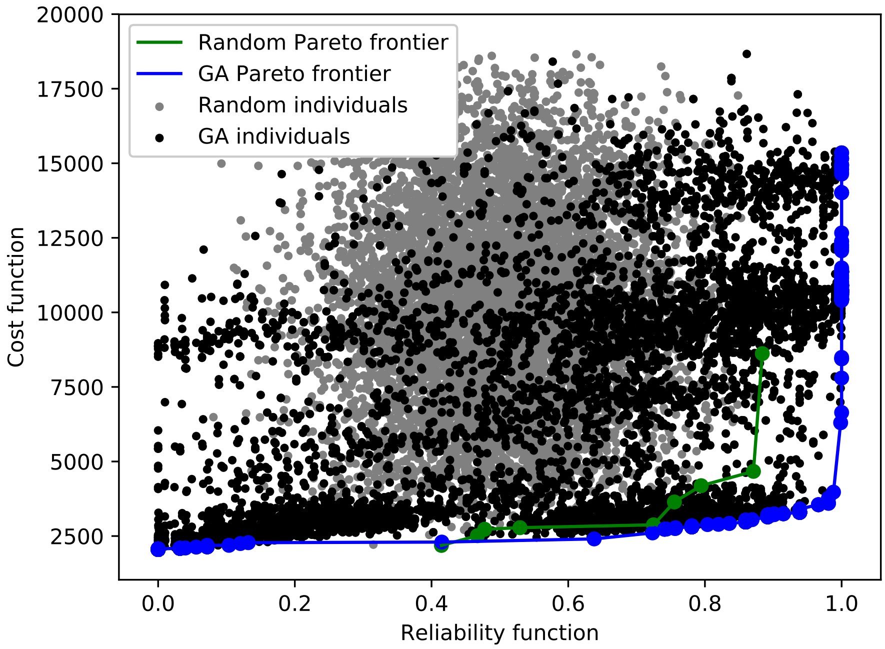

Figure 3.16: Comparison between the Pareto frontiers generated using a GA and a random search respectively. The optimised values are obtained considering three objectives (minimise costs, maximise reliability, minimise cost/reliability ratio) and using the superposition approach.

Similarly, a method to visualize the effective directionality of the search consists in looking at both the overall distribution of the identified solutions during the GA and the results of the last generation, as illustrated in Figure 3.17. Here it can be seen how not only in each subplot the majority of the solutions is concentrated in the area where the objective is predominantly satisfied, but also how the last generation is focused in the area that mostly satisfies that objective. However, also a degree of spread over the individuals of the last generation can be noticed, which might indicate that the GA has not fully converged yet.

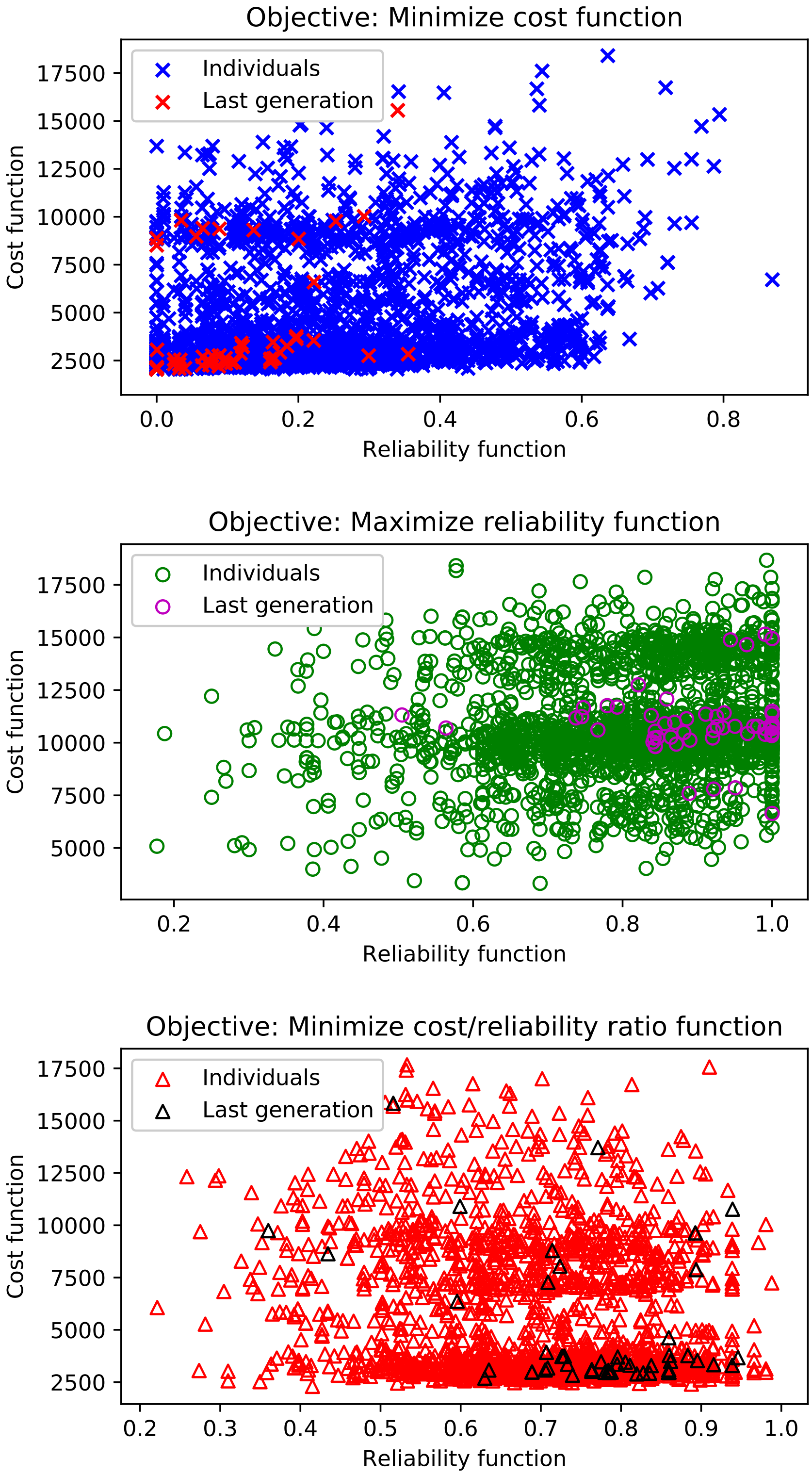

Figure 3.17: Distribution of generated solutions, with last generation highlighted, for three objectives (minimise costs, maximise reliability, minimise cost/reliability ratio) using the superposition approach. It is shown how the choice of different objectives guides the search towards different areas of the search space.

Once that the effectiveness of the generic implemented GA is demonstrated, the focus can be shifted towards checking the validity of the individual approaches.

The first approach, as described in Section 3.2.3, consists in combining the results of several single-objective optimisations in order to take advantage of the different directionality of each search procedure shown in Figure 3.17. Hence, once all the results are merged together, a larger set of possible solutions to the proposed problem is identified. The full objective space explored in this way is much larger with respect to that explored in each individual optimisation, providing a comprehensive assortment of solutions to define the best arrangements for the offshore farm. This concept, previously exemplified in Figure 3.10 where only the areas were highlighted, is shown in Figure 3.18, where the 2-dimensional projections of the identified solutions are plotted.

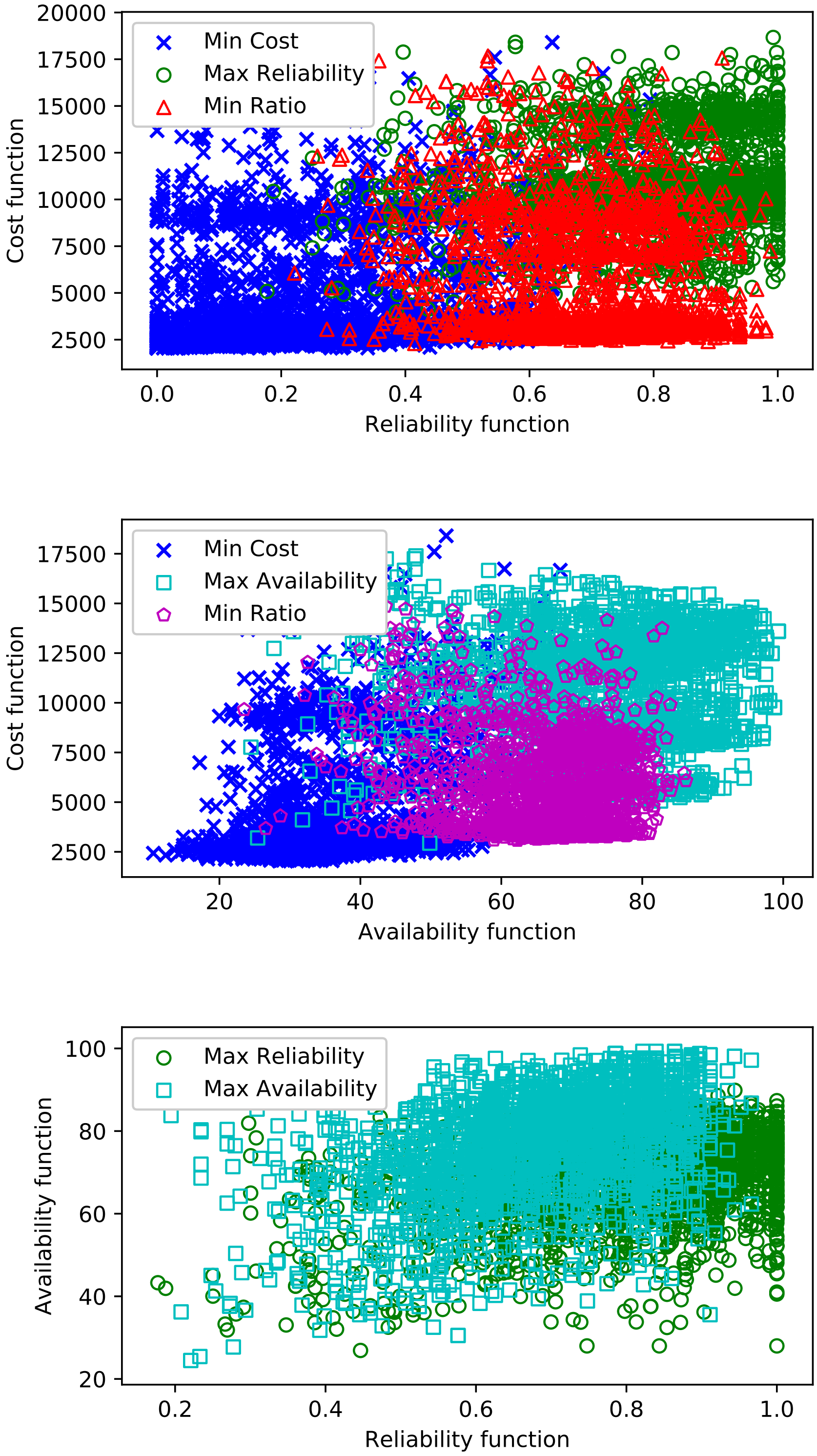

Figure 3.18: 2D distributions of all generated solutions throughout the optimisation, using the superposition approach, in function of the different objectives.

From these charts, the Pareto frontiers, containing the non-dominated solutions where one objective cannot be improved without degrading the other, can be identified as shown in Figure 3.19.

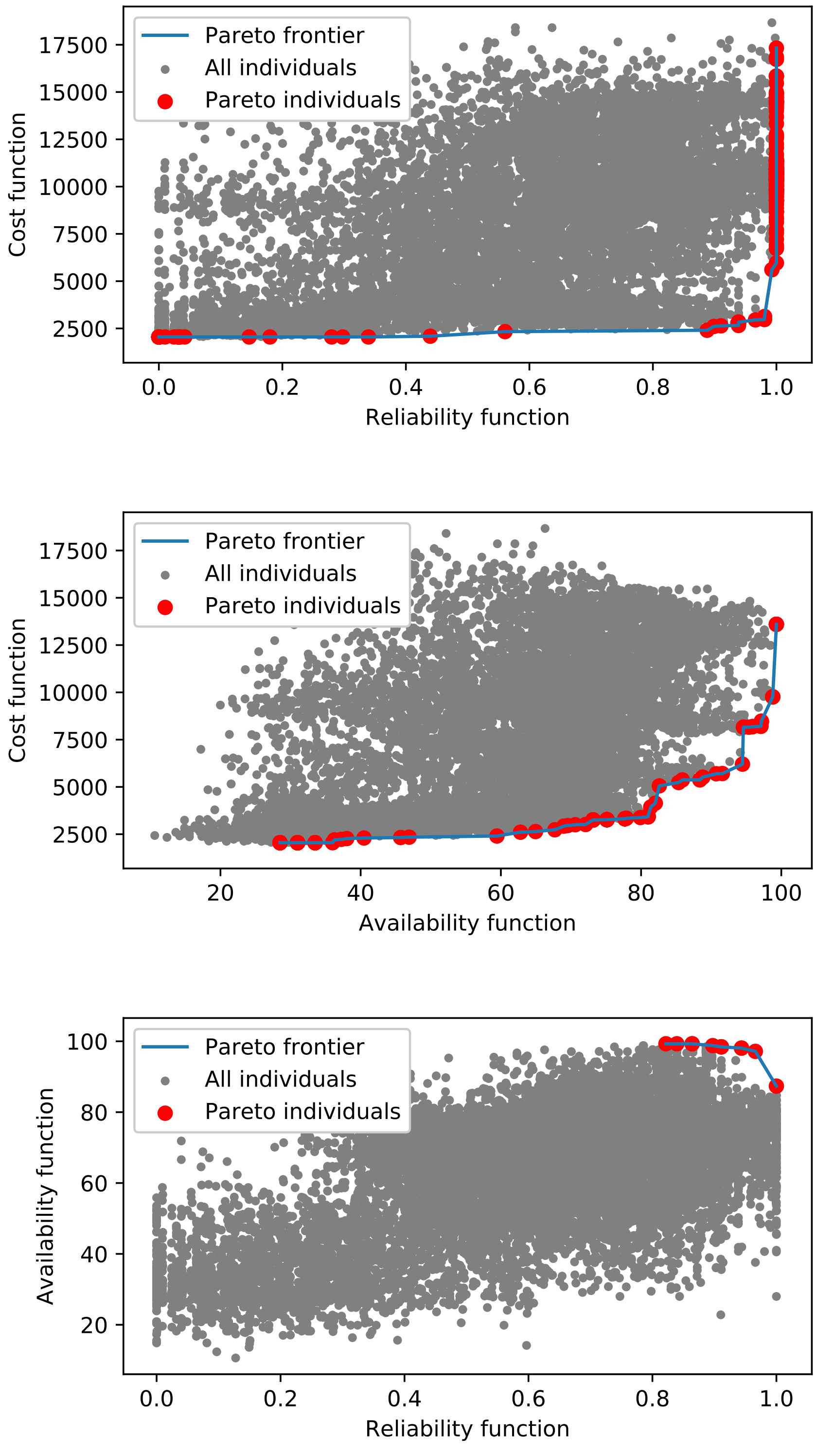

Figure 3.19: 2D distributions of generated solutions with Pareto frontiers highlighted, using the superposition approach, in function of the different objectives.

Thus, the Pareto frontier can be presented to a decision-maker who will be able to select one of the non-dominated solutions lying on it depending on his/her requirements and preferences. At this point, the solution can be decoded in terms of the combination of assets that originated it.

Pareto frontiers are also an useful way to obtain an ulterior proof of the implemented GA as an effective optimisation method. The evolution of the Pareto frontiers along generations can be followed to check if the quantity and quality of the non-dominated solutions is increasing, as illustrated in the example in Figure 3.20. Here the Pareto frontier moves towards the area with lower cost and higher availability as the number of generation increases, meaning that the implemented algorithm is actually producing optimised solution during its evolutionary search. As a result, also the evolution of the Pareto fronts could be used as a stop criteria for the GA, by running it until the Pareto frontier stops improving.

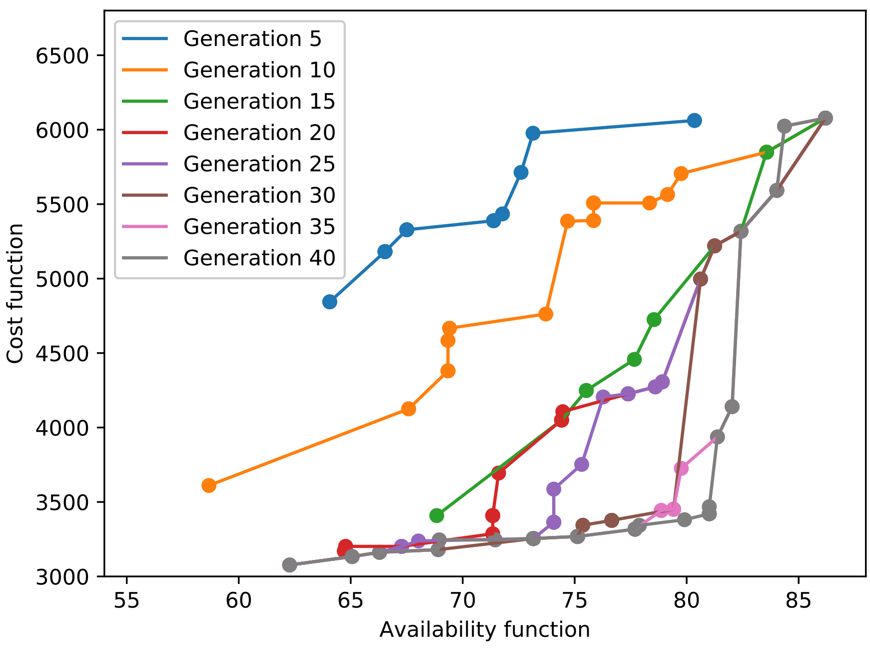

Figure 3.20: Evolution of the Pareto frontiers through generations for the cost/availability chart.

Ideally, the individuals of the last generation should include all the Pareto solutions found during the optimisation, otherwise the algorithm is not preserving the best solutions. However, if the GA is *generational*, i.e. also temporal or intermediate populations are used in order to obtain the full scenario, solutions that are good with respective to an objective may be discarded if they are measured against an other objective. If necessary, a *steady state* GA can be used in alternative, where only one population is considered and all the individuals of a new generation (offspring) are measured against all the current individuals according to all objectives, and kept only if these are better using a replacement algorithm. This slows down the GA but preserves Pareto solutions through all the generations (Chafekar *et al.*, 2003).

Several 2D charts are generally preferred to a single 3D chart in order to visualize the direct correlations between two objective functions. However, despite it is often more difficult to grasp the relationship and corresponding values for three objective functions at a time, the results can be plotted on a 3D chart. In Figure 3.21 the same results used to plot Figure 3.18 are visualised in a series of 3D plot including only 20 individuals, only one population and all the five populations obtained in the first GA approach respectively, in order to give an idea of this difficultness.

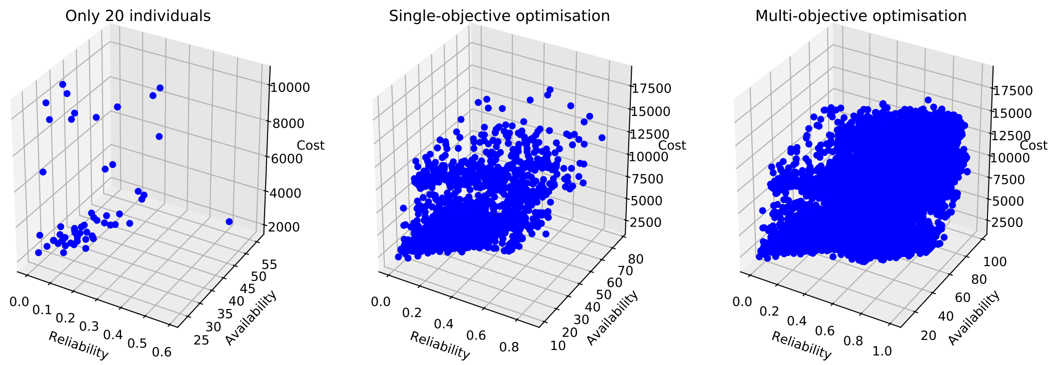

Figure 3.21: 3D distributions of generated solutions, using the superposition approach, in function of the different objectives. 20 individuals, only one population (minimise costs) and all the five populations obtained in the first GA approach are considered respectively.

Similar to the 2D versions, also from the 3D visualisation of all the investigated solutions the non-dominated ones can be identified, as shown in Figure 3.22. However, characterising the trade-offs with respect to all three objectives can be more challenging using these 3D charts.

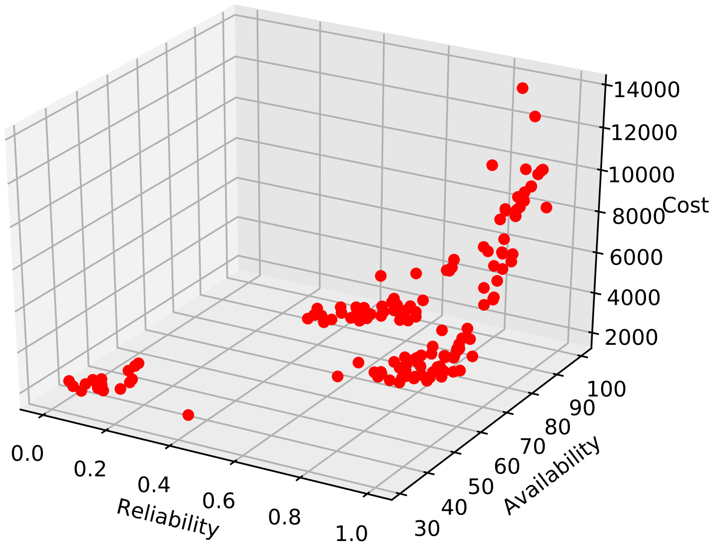

Figure 3.22: 3D Pareto solutions in function of the different objectives.

When the other approaches are implemented, a similar series of tests can be performed in order to verify the effective execution of the optimisation algorithm. In addition, a series of density plot can be used in the weighted sum approach in order to check on the directionality of the search with respect to the weights imposed, as illustrated in Figure 3.23. Here, the different solutions obtained when the weights are iteratively changed, can be observed. However, the solutions are shown in terms of only two of the three weights used in the GA, but all of them should be taken into account in order to correctly interpret the directionality of the search procedure.

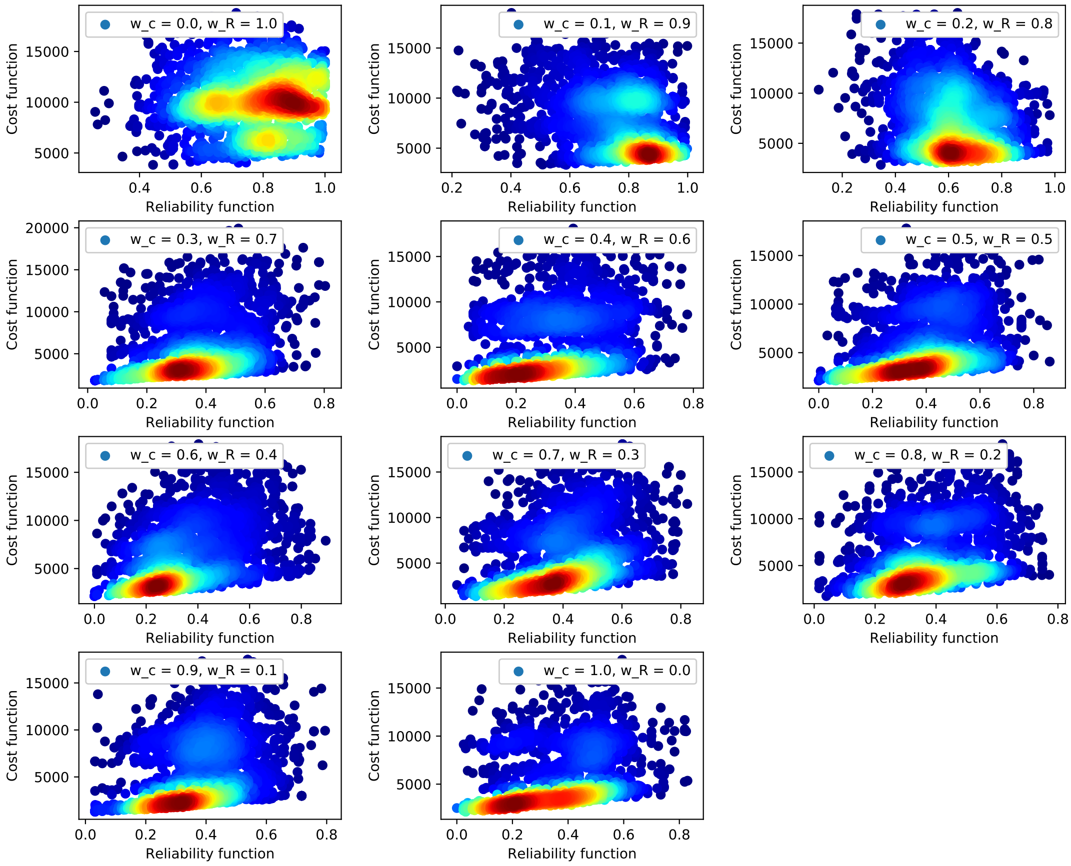

Figure 3.23: 2D density plots of generated solutions, using the weighted sum approach, in function of the different objectives and different weights. *(w_c = cost weight; w_r = reliability weight)*.

Finally, similar to the verification on the effectiveness of several single-objective optimisations in the superposition approach, a last check can be done for the VEGA inspired method in order to verify that two sub-approaches are actually useful in order to obtain a more complete overview (and therefore a larger Pareto front) of the investigated search space. This can be verified in Figure 3.24, where the results of the two optimisations are distinguished in order to highlight how the two sub-approaches described at the end of Section 3.2.3, here indicated as *elitism* and *roulette wheel* respectively, explore different areas contributing to the attainment of a larger search space.

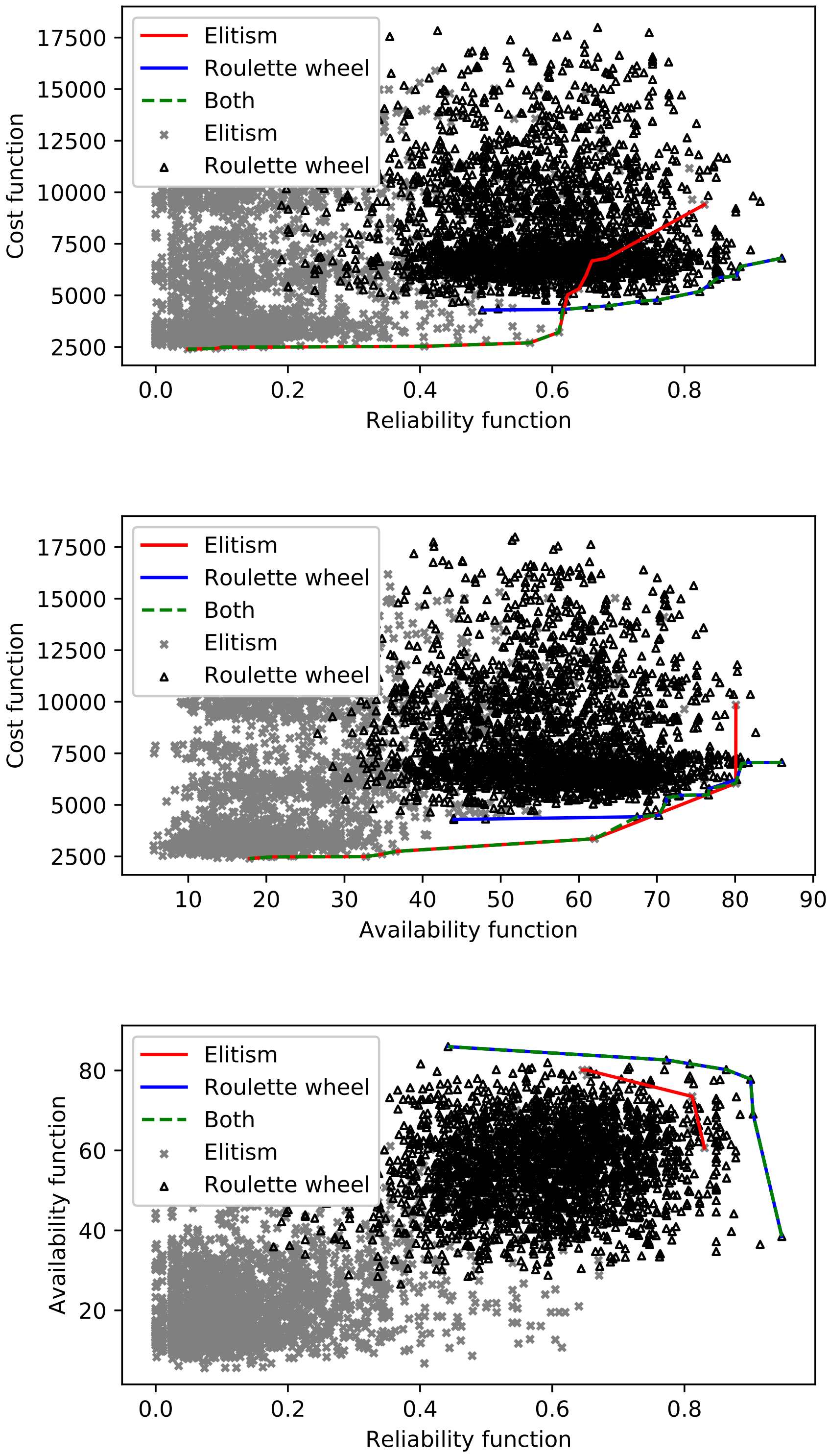

Figure 3.24: 2D distributions of generated solutions, using the VEGA approach, in function of the different objectives and different sub-approaches. Pareto frontiers are highlighted for the two sub-approaches (both jointly and individually).

3.2.5 Approach selection

Given the formulation of the chromosome, its relationship to the O&M strategy input parameters, and the objective functions, the three multi-objective GA approaches described are compared in order to provide an example of approach selection. For the comparison, the generated Pareto fronts are evaluated against these criteria: the more solutions in the area of the desired trade-offs (e.g. minimum cost/maximum reliability or maximum availability/maximum reliability) the better. This concept can be better visualised in Figure 3.25. In this figure, the Pareto fronts obtained for the three approaches are plotted considering only two objectives at a time in order to aid clarity. The knee of the Pareto curves have been enlarged as, for the investigated problem, this is a key area of interest for a decision-maker. This area includes those solutions that provide the most even trade-offs between the two objectives considered in each chart (e.g. maximum reliability at the minimum cost). It has to be remembered that though the presented plots look at projections onto two dimensions, all the solutions are considering all three objectives. Nonetheless, if for any reason one of the objectives is less relevant to the decision-maker, the choice can be moved towards the other values on the Pareto (e.g. minimum cost regardless of reliability or availability values). It is important to note that though realistically a decision maker might generally be concerned with the knee, this is not always the case and in various situations the extents and shape of the Pareto front also aid in the decision making process.

From the enlargements in these figures, the most effective approach in the search of limit solutions in this example is the one exploiting the weighted sum method. Despite very similar computational times, the solutions found with this method provide lower extremes in the cost/reliability and cost/availability Pareto fronts, as well as higher extremes in the availability/reliability Pareto front. Thus, although other approaches may provide more solutions on the Pareto, preference is given to this method due to the presence of solutions lower in cost, considered as a more valuable objective over the others, in the selected reliability and availability ranges. These quantitative decision criteria are illustrated in Table 3.3, where the minimum cost is in the selected reliability range, the minimum cost in the selected availability range, and the maximum availability in the selected reliability range are reported for Figures 3.25a, 3.25b and 3.25c respectively.

These are generic guidelines provided to explain how to interpret and compare the results of different optimisation approaches. Nonetheless, selection criteria may vary depending on the specific case analysed and the preferences of the decision-maker. In fact, despite the example above provided, the establishment of what is best for the search procedure, as well as the attainment of valuable results, is relative and problem dependent. As a consequence, a choice needs to be made depending on the specific context and related constraints, i.e. resources available and desired outcomes.

Table 3.3: Values of solutions in the ranges selected according to the preferences of the author for example in Figure 3.25.

Criterium/approach	**S**	**W**	**V**
Minimum cost in reliability range 0.843 - 0.844 (Fig.3.25a)	35546	14157	126096
Minimum cost in availability range 64 - 68 (Fig.3.25b)	40417	22209	71869
Maximum availability in reliability range 0.835 - 0.845 (Fig.3.25c)	69.06	69.81	58.45

Legend: **S** = Superposition, **W** = Weighted Sum, **V** = VEGA inspired.

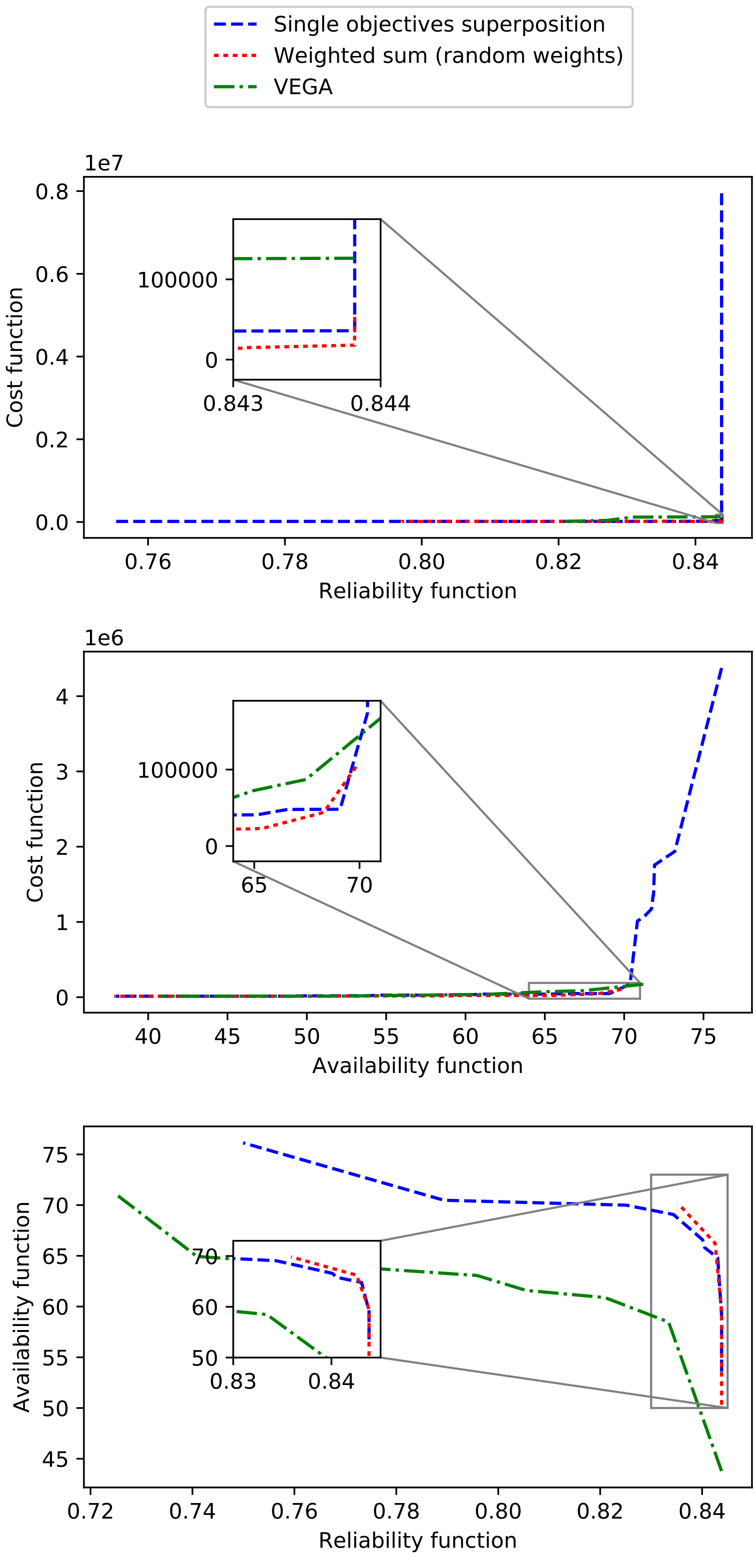

Figure 3.25: Comparison of the Pareto frontiers obtained using the three approaches.

Chapter 4

Applications and results

Contents

After having provided an overview of the characterisation and optimisation tools implemented in this work, a selection of case studies is presented in order to demonstrate the capabilities and implications provided by the two models, as well as the links between them. Thus, the characterisation of an ORE farm and the estimation of its main key performance indicators, together with proposals to improve the profitability of the project, are presented in Section 4.1. The case study implemented to both verify the characterisation tool and benchmark the objective functions of the optimisation tool described in Chapter 3, is presented in Section 4.2. Here, it is shown first how confidence has been built in the characterisation model and second how this has then be used to calibrate the evaluation functions used for the optimisation. Finally, a case study to show the applicability of the optimisation model as an effective way to improve the profitability of an ORE project, in a quicker and more comprehensive way compared to a manual proposal of suitable alternatives for the current assets, is provided in Section 4.3. For each case study, the scenario, input data, results and broader discussion of the outcomes are provided. A more detailed discussion on the significance of the results of the individual models, and the implication of this coupled approach, follows in Chapter 5. In order to provide an overview of the models with different ORE technologies, the first case study concerns a tidal energy farm, while the second and third an offshore wind energy farm. An example of case study concerned with wave energy technology is provided in Appendix A.

4.1 Case study 1 - Characterisation of an ORE farm

The first case study consists in analysing an ORE farm using the characterisation model described in Section 3.1. After introducing the scenario and the inputs collected for the study, the key performance indicators obtained with the tool are presented. As a result, an overview of the main considerations that a decision-maker could make in order to assess the effectivity of the current O&M and farm assets, as well as propose interventions aimed at improving these, is discussed.

4.1.1 Scenario

The offshore farm considered for this case study is a small array of tidal stream devices (TSD) consisting of two identical devices. According to a series of technical and environmental constraints, the identified location is a channel in the Inner Sound of the Pentland Firth, between Stroma Island and the north Scottish mainland, as shown in Figure 4.1. The offshore site has been selected as it is suitable for tidal energy projects, as demonstrated by the recent Meygen project, which aimed to deploy the first commercial array of tidal stream turbines in the UK (Magagna & Uihlein, 2015). Given this offshore location, the data sources for the MetOcean data, device specifications, and the prescribed maintenance vessels are described in the following section.

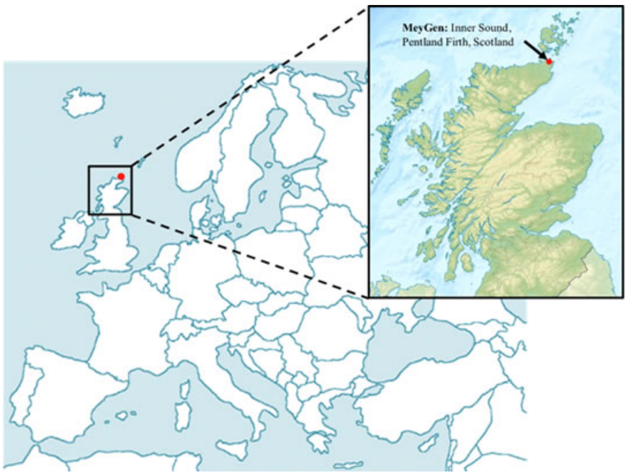

Figure 4.1: Selected location for the tidal farm. Image from Meygen webpage (Meygen website, 2017).

4.1.2 Input data

4.1.2.1 Location and MetOcean data

The MetOcean data to characterise this site are retrieved using a range of methods. As regards the wave and wind measurements, that are used by both the decision support model and Mermaid to establish times and limits of the offshore operations, these are retrieved using the numerical simulation model WAVEWATCH III (Tolman *et al.*, 2002). As for the tidal current measurements, which are more relevant for this project as they not only define the operational limits of the vessels, but also provide the resource data which dictate the energy produced from the devices, these are extrapolated from one month of Acoustic Doppler Current Profiler (ADCP) data. These measurements are then used to reconstruct a complete time series for the considered lifecycle of the farm (10 years) using the MATLAB routine UTide (Codiga, 2011), which is based on harmonic analysis of the tide components.

4.1.2.2 Device

With regard to the device, the TSD considered in this work is a sea-bed fixed single turbine with permanent magnet generator, inspired by the Atlantis Resources (AR) series (Atlantis Resources Ltd. website, 2017). More specifically, the fictitious device selected for this work is adapted from the AR1000 tidal turbine using the information publicly available. This model is depicted in Figure 4.2.

The information related to the structure and taxonomy of the tidal stream turbines, as well as the related reliability data, are extracted from Delorm (2014). The power curve of the turbine has been obtained imposing a cut-in water speed of 1 m/s, a cut-out water speed of 5 m/s and a water velocity corresponding to the output power rated of the turbine (1 MW) of 2.65 m/s. The power curve between cut-in velocity and rated velocity has been reconstructed using the least squares method as mentioned in Section 3.1.1.1. A visual summary of the TSDs taxonomy, with subsystems and assemblies considered, is shown together with the RBD of the device in Figure 4.3. The power curve of the TSD and the current speed distribution of the site are illustrated in Figure 4.4. The considered tidal farm is assumed to consist of two identical devices of this kind, positioned in the offshore location at an inter device distance so as to minimise interference in the use of the resource and possible wake effects.

Figure 4.2: AR1000 horizontal axis tidal turbine. Image from Atlantis Resources Ltd. website (2017).

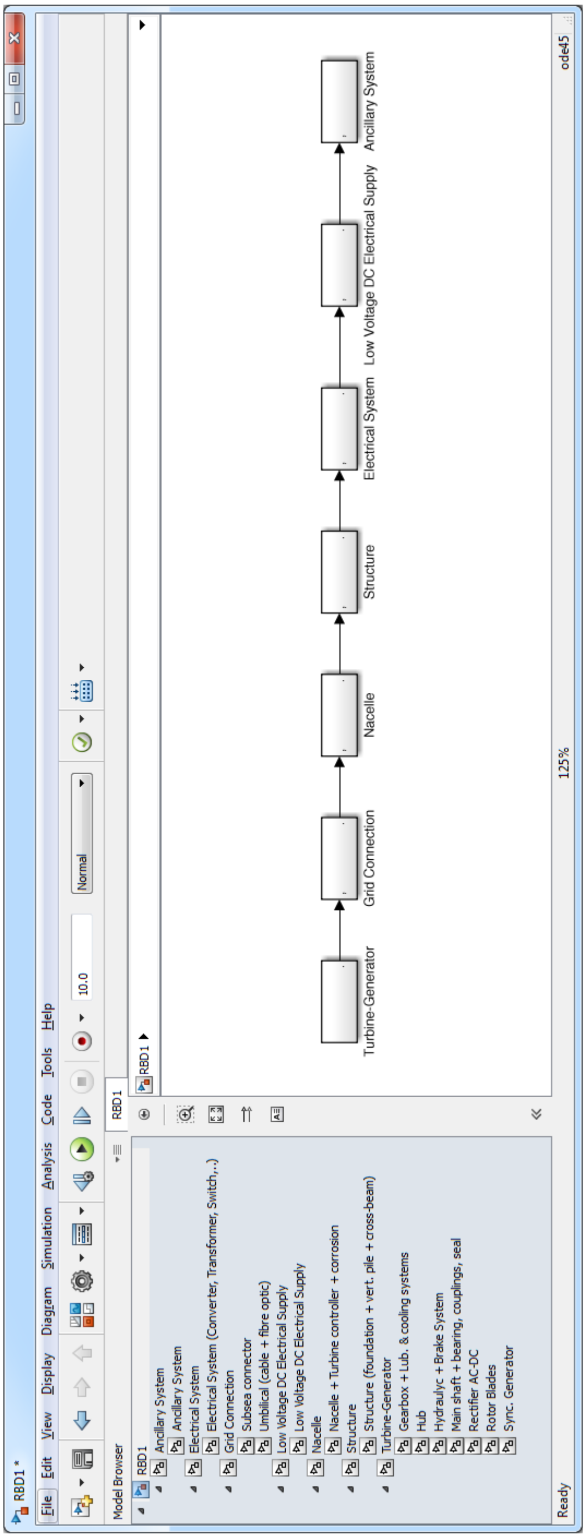

Figure 4.3: Reliability Block Diagram (RBD) in Simulink showing the considered subsystems of the device.

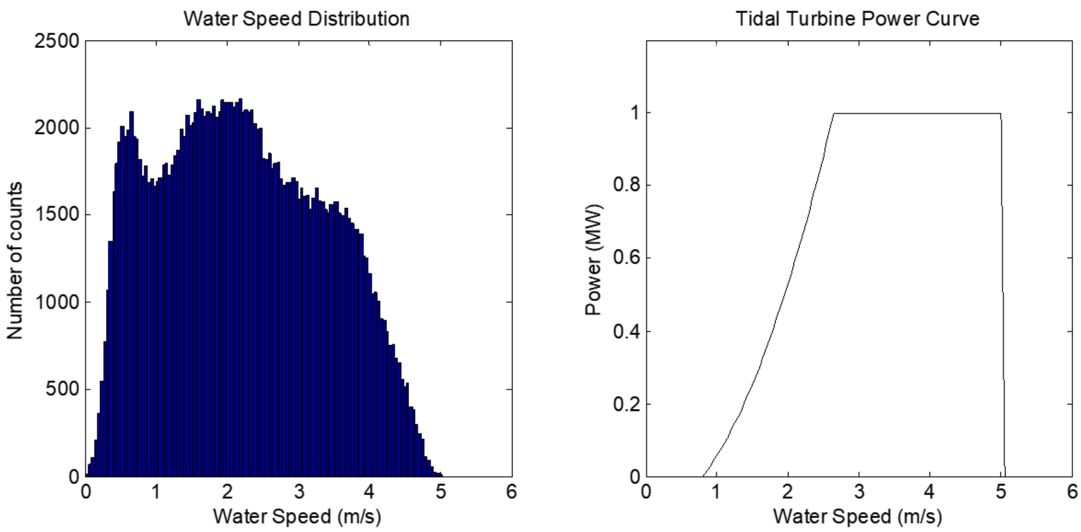

Figure 4.4: Water velocities distribution of the selected location and Power curve of the considered TSD.

4.1.2.3 Access systems

The capabilities of the rented or purchased O&M vessels are a key determinant of the lifecycle costs of marine renewables. While a fleet composed by different kinds of access systems can be considered in the characterisation model, in this case study two different offshore utility vessels, the Dart Fisher offshore supply ship and the HF4 vessel, have been compared in the analysis of the various O&M procedures for the two devices. The Dart Fisher belongs to a category of offshore utility vessels providing specialist crew, cargo transfer and multi-purpose support in the offshore renewables and oil & gas industries (Dart Fisher, 2017). The second is a vessel capable of operating in extreme offshore environments, designed and proposed by Mojo Maritime Ltd., but not yet manufactured (HF4, 2017). The relevant specifications of the two vessels are summarised in Table 4.1, while those of the subsystems and components considered for the study, adapted from the work of Delorm (2014), in Table 4.2. The port selected for all the maintenance operations is the multi-purpose Scrabster harbour (Scrabster Harbour, 2017), located off the north coast of Scotland approximately 25 km from the offshore location designated for the deployment of the tidal farm.

Table 4.1: Vessels information used for the analysis.

	HF4	Dart Fisher
Day Rate (£)	2500	6000
Maximum Wave Height to Access and Leave Port (m)	3.5	3
Maximum Wind Speed to Access and Leave Site (m/s)	15	15
At-Site Station keeping Limits		
Tidal Current (m/s)	5	2
Wave Height (m)	3.5	3
Wind Speed (m/s)	17	15

Table 4.2: Components information used for the analysis.

Sub-assembly/Component	Subsystem	Annual failure rate
Rotor Blades	1.Turbine/Generator	0.230
Hub	1.Turbine/Generator	0.250
Main shaft + bearing, couplings, seal	1.Turbine/Generator	0.055
Gearbox + Lub. & cooling systems	1.Turbine/Generator	0.134
Hydraulic + Brake System	1.Turbine/Generator	0.031
Rectifier AC-DC	1.Turbine/Generator	0.001
Sync. Generator	1.Turbine/Generator	0.271
Subsea connector	2.Grid connection	0.009
Umbilical (cable + fibre optic)	2.Grid connection	0.127
Nacelle + Turbine controller + corrosion	3.Nacelle	0.269
Structure (foundation + vert. pile + cross-beam)	4.Structure	0.150
Electrical System (Converter, Transformer, Switch,..)	5.Electrical System	0.580
Low Voltage DC Electrical Supply	6.Electrical Supply	0.152
Ancillary System	7.Ancillary System	0.120

4.1.3 Results

In this section the results obtained simulating the lifecycle of the tidal farm are reported in relation to the two O&M vessels selected for this study. A short discussion on the results obtained along with a number of potential optimisation extensions will follow in Section 4.1.4.

4.1.3.1 Reliability

This section shows the results obtained in terms of the reliability of the subsystem and single components considered in the taxonomy of the device. The first chart in Figure 4.5 shows the values of reliability and Mean Time To Failure (MTTF) for each component. The values of reliability, in the range [0, 1], are calculated at the end of the assumed lifetime of the device. This should not be confused with the actual lifetime of the individual components. The same information, including a list of the number associated with each considered component of the device, is shown in Table 4.3.

Table 4.3: Identification number, reliability at the end of the considered lifecycle (10 years) and MTTF for each component of the device.

#	**Component**	**Reliability**	**MTTF** [$\times 10^6$ **hours**]
1	Rotor Blades	0.100	0.038
2	Hub	0.080	0.035
3	Main shaft + bearing, couplings, seal	0.570	0.159
4	Gearbox + Lub. & cooling systems	0.260	0.065
5	Hydraulics + Brake System	0.730	0.282
6	Rectifier AC-DC	0.980	5.840
7	Sync. Generator	0.060	0.032
8	Subsea connector	0.910	0.973
9	Umbilical (cable + fibre optic)	0.280	0.069
10	Nacelle + Turbine controller + corrosion	0.060	0.032
11	Structure (foundation + vert. pile + cross-beam)	0.220	0.058
12	Electrical System (Converter, Transformer, Switch,..)	0.003	0.015
13	Low Voltage DC Electrical Supply	0.210	0.057
14	Ancillary System	0.300	0.073

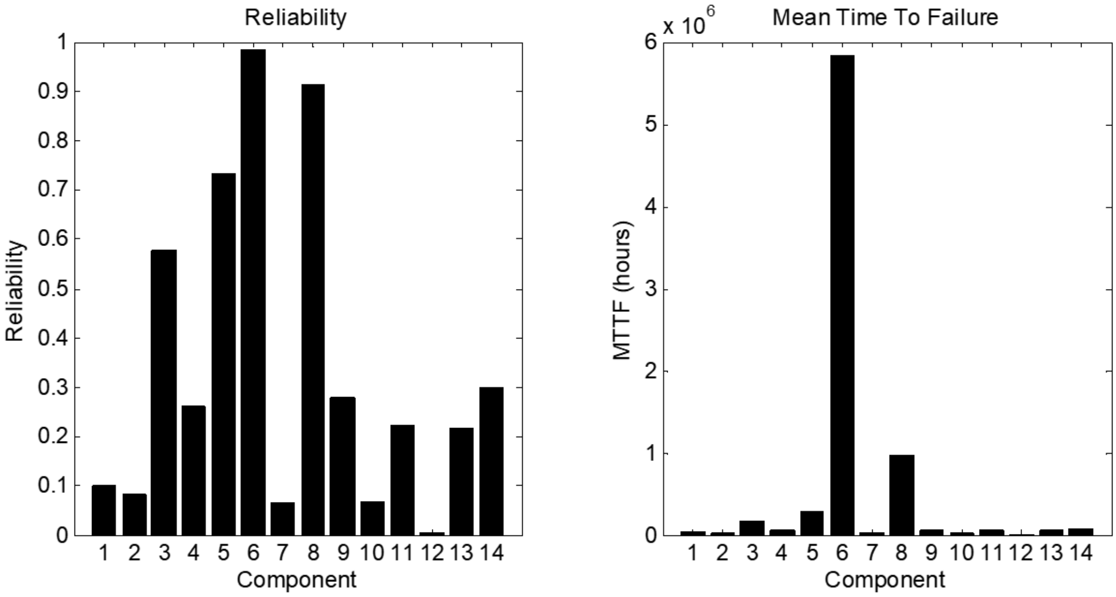

Figure 4.5: Reliability at the end of the considered lifecycle (10 years) and MTTF for each component of the device.

Although a number of items will inevitably be connected in parallel in the real turbine, all subsystems have been considered in series according to the adopted taxonomy and the criticality requirement of each component of the device, as defined in Section 3.1.3.3. Furthermore, though in a real system some components might experience a limited or partial level of functioning as a consequence of a failure, in this analysis only two states of operation have been considered: fully working or not working in any capacity. This approach, in the case in which any partial failure is modelled as a full failure, leads to a conservative estimate regarding reliability and associated maintenance cost, i.e. low reliability and therefore overestimation of maintenance costs. Under these assumptions, it emerges that the most reliable components are the AC/DC Rectifier, followed by the subsea connector. In contrast, the least reliable is the electrical subsystem. This result is also observable in Figure 4.6, where the total number of failures for each component during the whole lifetime are shown for the two vessels under consideration. From the same figure it can be noticed how generally less failures happen with the Dart Fisher vessel. In this specific case, this is due to the minor capabilities of the vessel which, in turn, lead to slower repairs and higher downtimes (it should be noticed that in the implemented model failures can only occur when the device is working).

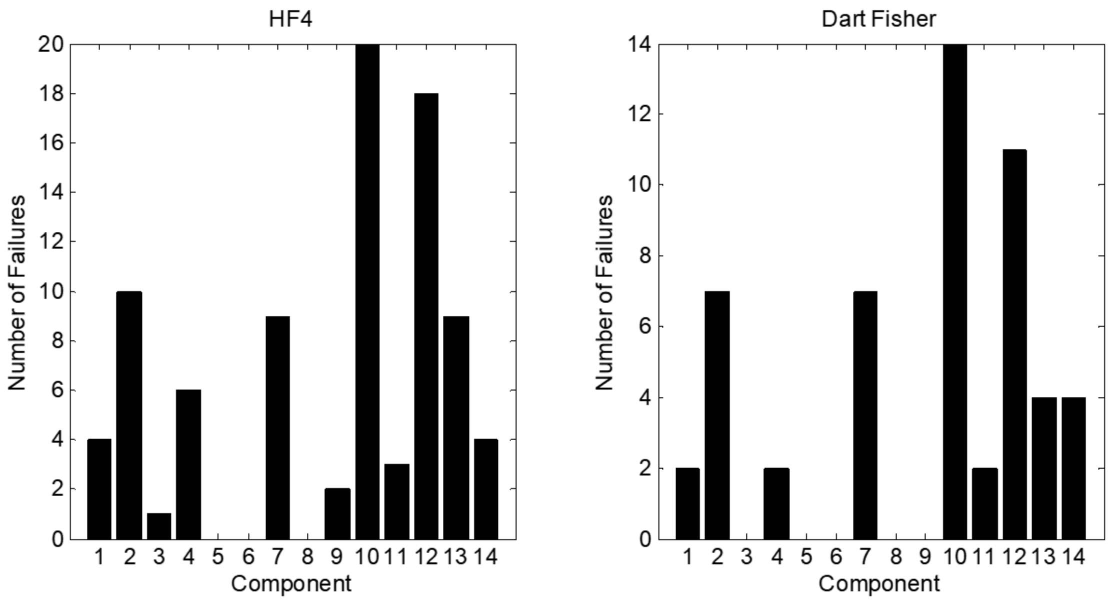

Figure 4.6: Total number of failures per component. Comparison between the two maintenance vessels.

More significant considerations on the reliability of each component may be found looking at the bar chart in Figures 4.7 and 4.8, where the contribution of each component to the unavailability of the tidal farm is analysed more in detail. In particular, a distinction is made between the percentage contribution to the total number of failures and the total downtime caused. In this way, it is possible to identify those components that fail more often, but more importantly those that result in a greater downtime. The efforts of the device designers should therefore focus especially on the latter. In this case the component which most contributes both to the total number of failures and the downtime of the devices is the electrical system of the tidal turbine. It can be seen that this is one of the few components for which the contribution to the total downtime is higher than the contribution to the total number of failures. In fact, the failures of this component alone induce more than the 40% of the total downtime of the devices when the HF4 is used (28% with the Dart Fisher). This is principally a result of the high number of constituent components within the electrical system, that contribute both to its sensitivity (then failure rate) and to the total amount of time needed to restore it in case of failure (procurement and repair or replacement time). In addition, similarly to most of the other components under consideration, it is assumed that the turbine nacelle has to be recovered in case of failures, extending the downtime due to weather windows requirements.

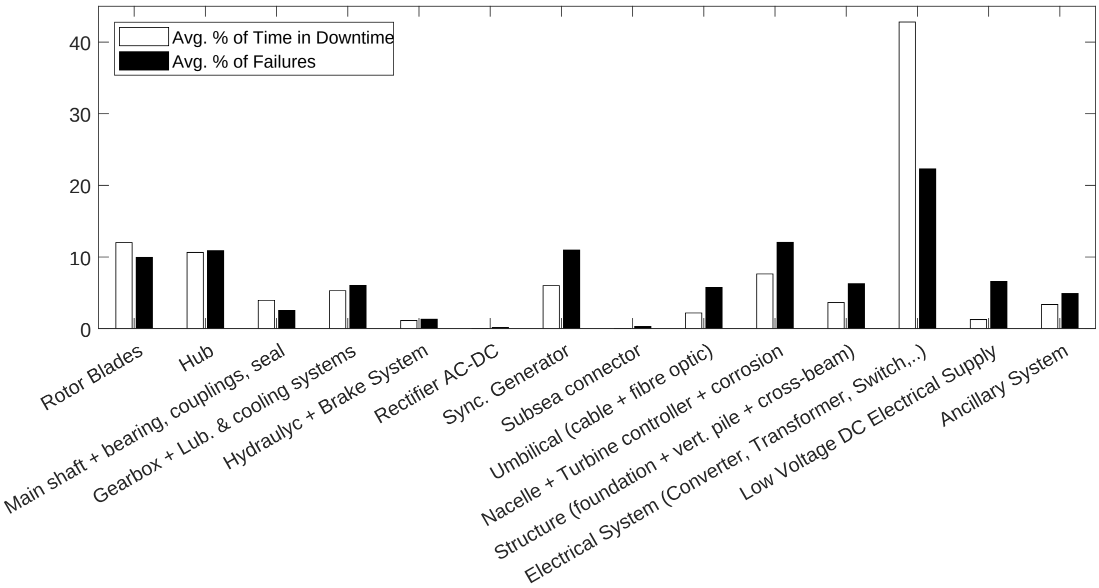

Figure 4.7: Average contribution of each component of the device to the total number of failures and the total downtime of the farm. In percentage, using the HF4 vessel.

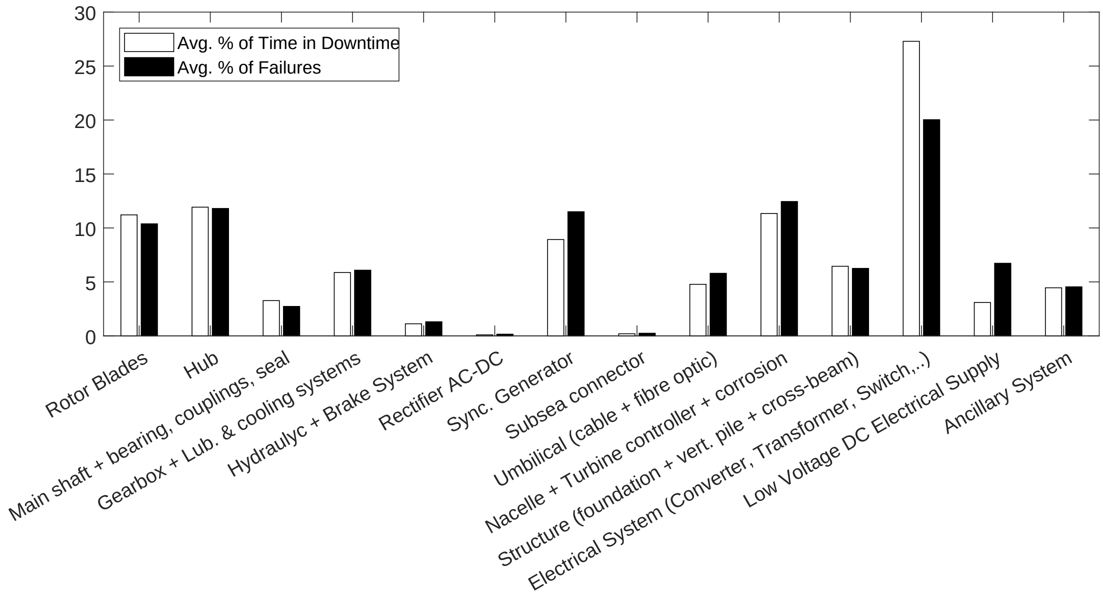

Figure 4.8: Average contribution of each component of the device to the total number of failures and the total downtime of the farm. In percentage, using the Dart Fisher vessel.

From these figures it is possible to quantify the importance of each component and prioritize the failures in terms of the RPN as described in Section 3.1.4, as shown in Figures 4.9 and 4.10.

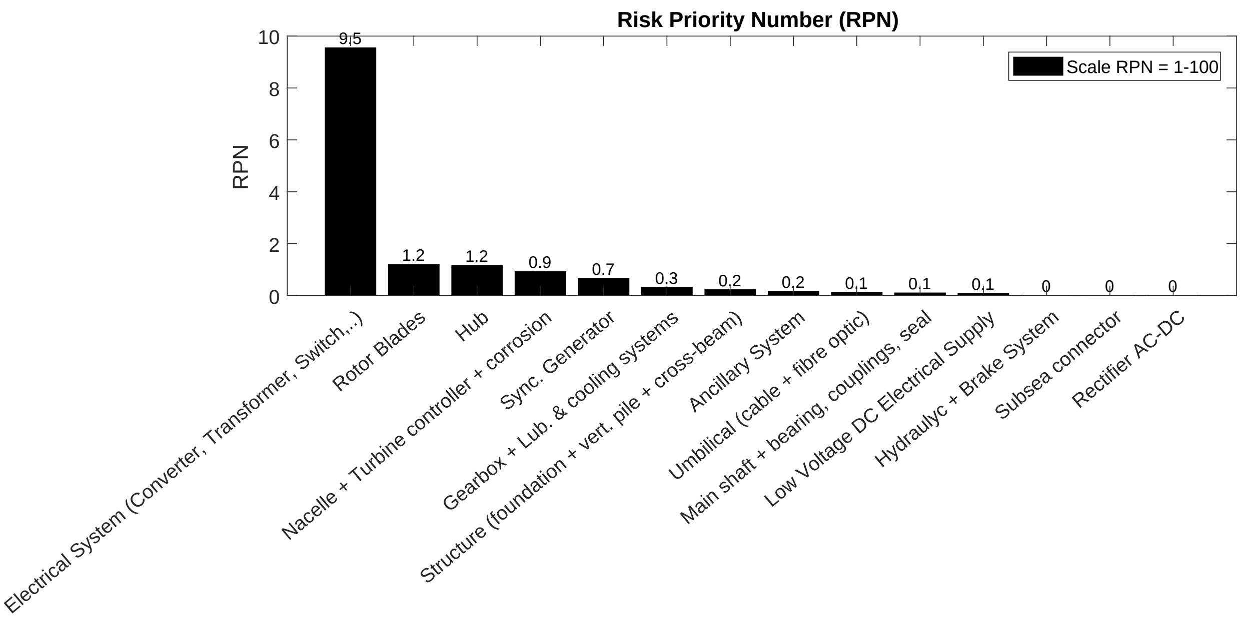

Figure 4.9: RPN of each component using the HF4 vessel.

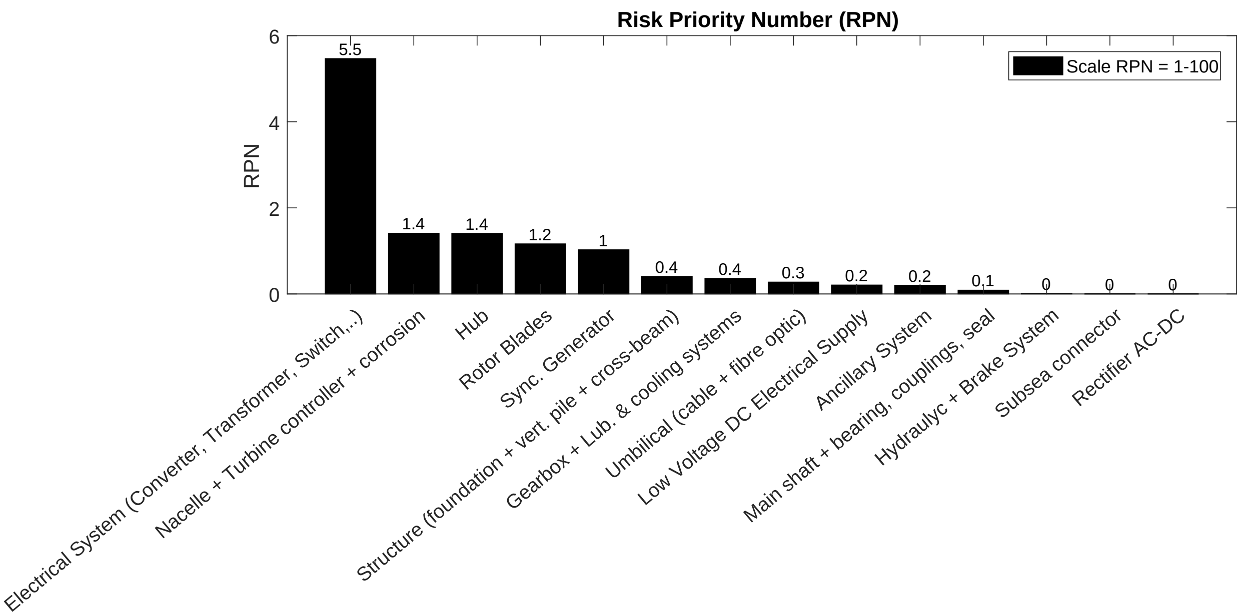

Figure 4.10: RPN of each component using the Dart Fisher vessel.

4.1.3.2 Energy production

The following charts show the results of the farm in terms of energy production, comparing the values obtained using the two different vessels for the O&M. Simulating the two devices over a ten year period results in an average energy production of 10060 MWh/year. This value has been estimated by applying the modelled power curve to the tidal current velocity time-series derived using UTide. All the unpredicted failures, as well as electrical and transportation losses, have been neglected for this calculation. This corresponded to an ideal capacity factor of 57.4% and 5030 equivalent hours, calculated respectively as:

$$Capacity\ Factor = \frac{Annual\ energy}{8760h \times P_{rated}} \tag{4.1}$$

and

$$Equivalent\ Hours = \frac{Annual\ energy}{P_{rated}} \tag{4.2}$$

The effects of the unexpected disruptions on the power production and the consequent maintenance operations are shown in terms of energy lost and downtime of the farm in Figure 4.11.

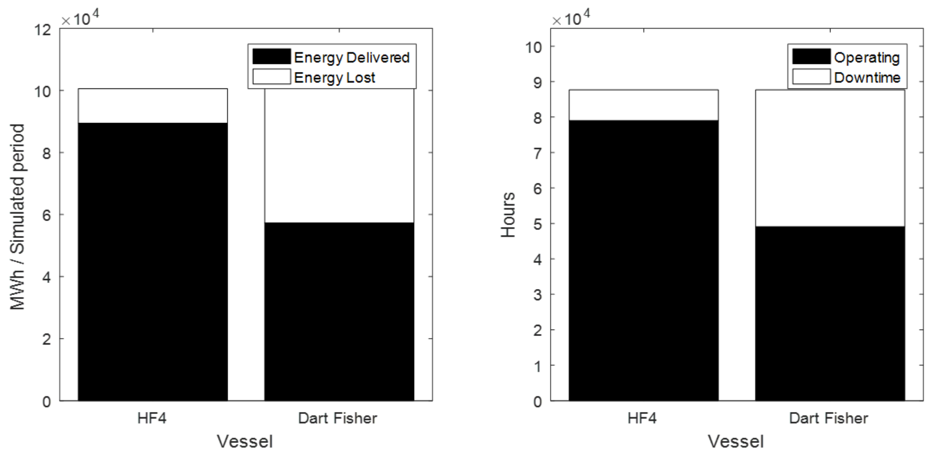

Figure 4.11: Relationships between energy delivered and energy lost due to failures, and between operating time and downtime, using the two maintenance vessels.

As it performs better across all performance indicators, it is clear that the HF4 is preferable for the considered offshore farm in order to reduce the lost production and the downtime due to unforeseen failures. The main reason for this advantage is the capacity of the vessel of operating in high tidal flows up to 5m/s. The same results can be analysed more in detail year by year, highlighting the difference in choosing one vessel or the other, as shown in Figure 4.12.

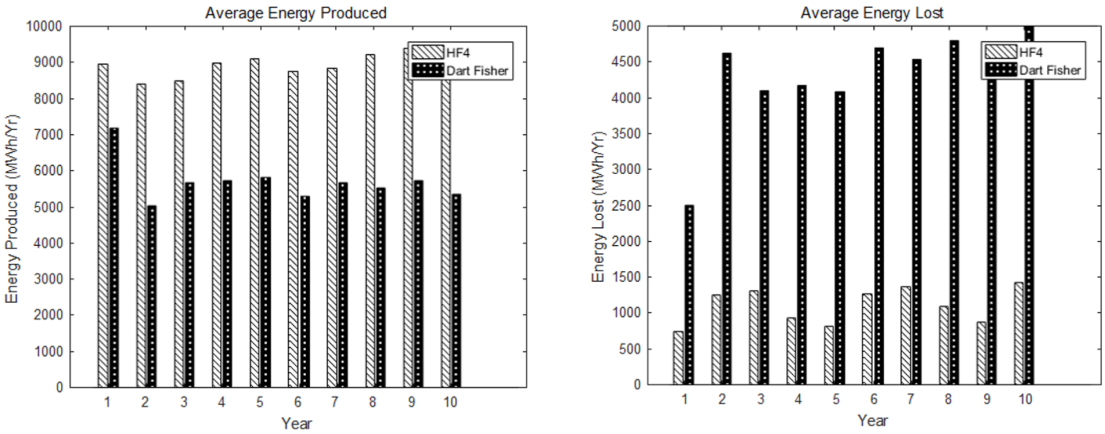

Figure 4.12: Annual average energy produced and energy lost. Comparison between the two maintenance vessels.

Analysis of these results is available also on a monthly basis. Turning to the availability of the farm, two types can be evaluated, namely time-based and energy-based. The first represents the ratio between the operational time of a device/farm and the total time considered:

$$Av_{time-based} = \frac{t_{UPTIME}}{t_{UPTIME} + t_{DOWNTIME}} \tag{4.3}$$

Likewise, the energy-based availability expresses the ratio between the real energy produced and the theoretical energy available:

$$Av_{energy-based} = \frac{Energy\ produced}{Energy\ available} \tag{4.4}$$

Both quantities are useful to evaluate the efficiency of the farm.

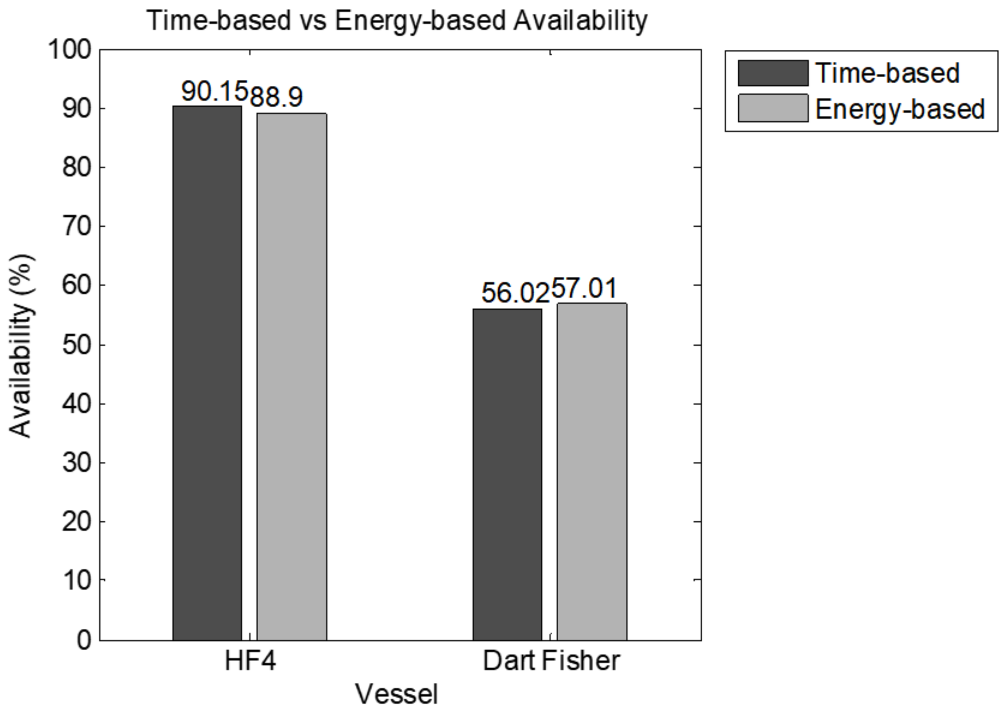

Figure 4.13: Time-based and energy-based availability for the tidal farm over its lifetime. Comparison between the two maintenance vessels.

Also this chart points out the higher effectiveness of the HF4 in the maintenance strategy of the devices. Even if the differences between the two vessels are considerable, curiously with the Dart Fisher the energy-based availability, which is more important since revenues are directly proportional to the quantity of energy sold rather than the amount of operating time, is higher than the time-based. This in some way underlines the good practice of making the devices available when the resource is higher, in order to minimise lost production.

4.1.3.3 Economics

A further series of results is produced in order to characterise the offshore farm from the economic point of view. This section illustrates the information that project managers can use to take decisions depending on the cost effectiveness of each choice. In order to produce financial estimations, a strike price for the electricity produced by the tidal farm has to be established. For this case study, this has been assumed according to the package of measures approved in 2012 by the UK Department of Energy & Climate Change (2013), which determined for the year 2015/16 a price of 305 £/MWh for the electricity produced by wave and tidal devices. Applying this price to the values in Figure 4.12, gives the detailed annual revenue due to the sale of electricity and the financial losses due to unexpected downtimes as shown in Figure 4.14.

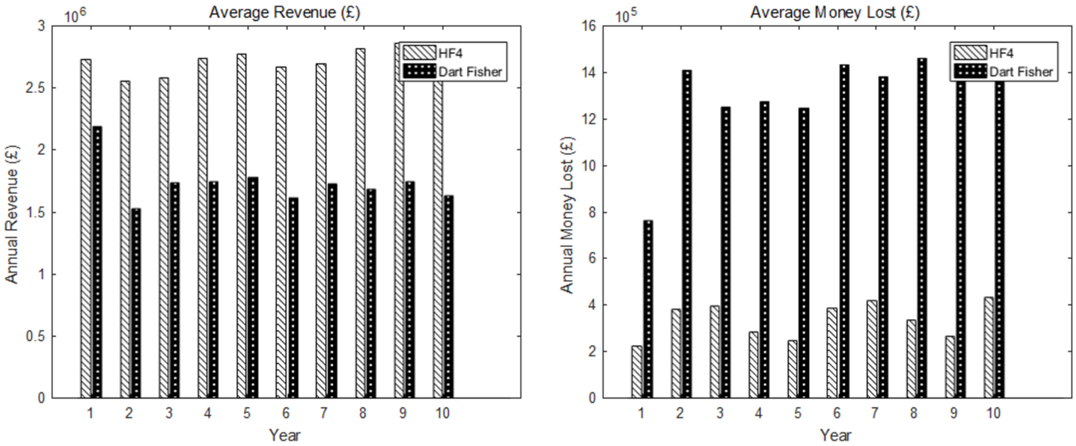

Figure 4.14: Annual average revenue and money lost. Comparison between the two maintenance vessels.

As these result represent statistical results from a stochastic method, the exceeding probabilities associated to these values can also be derived, as indicated in Figure 4.15. These figures are particularly useful in the risk assessment of a financial model, in order to obtain a statistical confidence level for the estimate. These quantities are known as P values (Probability values), and indicated as Pxx, where xx is a number. For instance, P90 denotes the value that is exceeded 90% of the time. Generally the P10, P50 and P90 values are of interest since they provide useful indications on the lowest, the median (or best) and the highest figure that should be achieved according to the predictions.

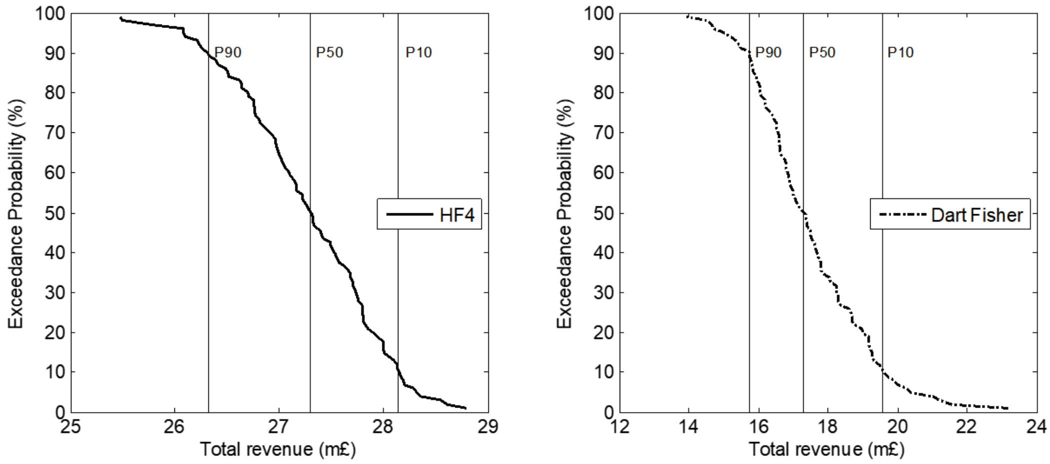

Figure 4.15: Exceedance probabilities on the total revenue of the farm. Comparison between the two maintenance vessel.

Figure 4.15 suggests again how the confidence of obtaining major revenue at the end of the lifetime of the farm is much higher using the HF4 vessel. In fact, using the HF4 the P50 of the total gross revenue is £27.28m, with lost revenue of £3.40m in respect to the ideal case of no disruptions, while using the Dart Fisher this is £17.49m, with estimated lost revenue of £13.19m. Similar exceedance probability analysis can be performed on other relevant parameters such as the energy delivered (or lost) and the financial losses, depending on the energetic or financial indicator that the decision-maker deems useful. For instance, an operator may want to know the probability that a certain target of production is achieved, while an investor may want to be sure that no more than a certain amount of revenue is lost.

4.1.3.4 Simulations

In order to produce reliable results without exceeding with the computational time required for the simulations, a suitable number of runs is sought for the Monte Carlo analysis. Each of these runs simulates the complete lifetime of the tidal farm taking into account all the mechanisms and constraints. Results are then averaged over the total number of simulations in order to obtain the most probable outcome for each parameter. Discrepancies and divergences are quantified at the end of the analysis in order to assess the level of confidence on the results obtained. A first indication of the convergence of the results can be visualised plotting the progressive average of relevant values considered, e.g. the power delivered and power lost considered in Figure 4.16.

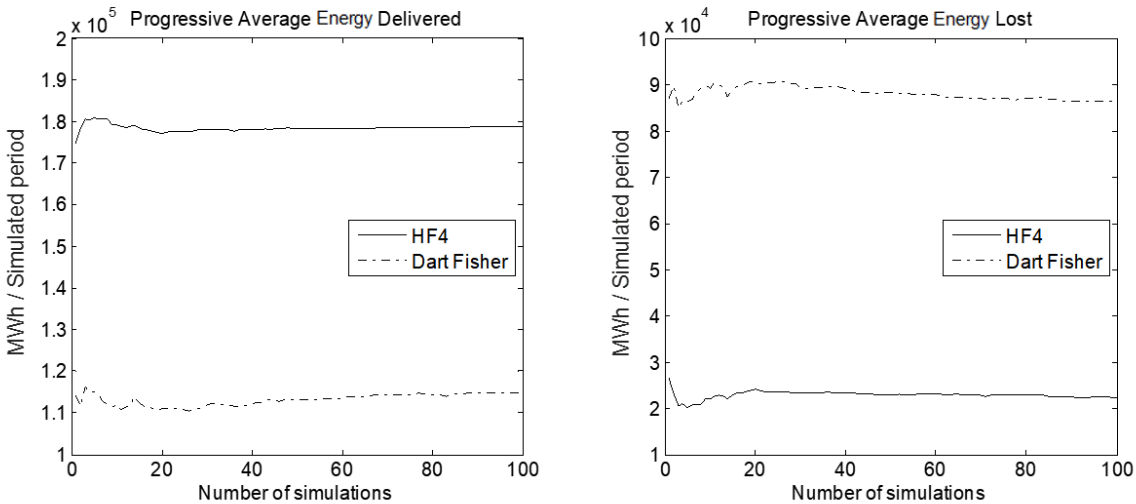

Figure 4.16: Progressive average through the simulations of the final values of power delivered and lost.

At first glance, the two trends seem quite flat, indicating no or very little variation between one simulation and the next. However, looking at the scale on the y-axis, this shows how even small variations in the graph can correspond to large differences of tens of thousands of MW. For this reason, it is useful to also look at the percentage changes, shown in Figure 4.17, for example on the power delivered (similar checks can be made also on other parameters).

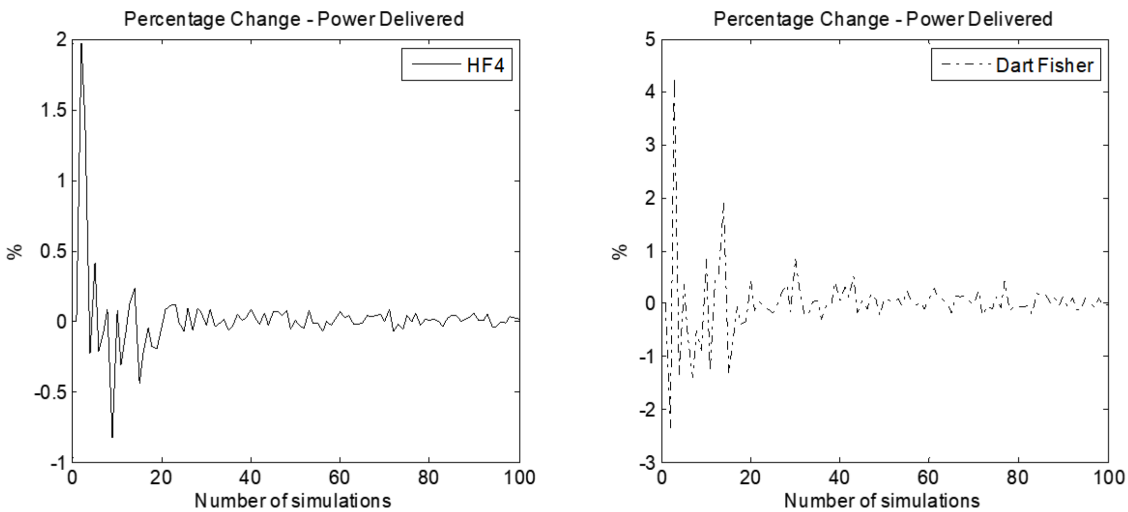

Figure 4.17: Percentage change in the average value of power delivered across the simulations. Comparison between the two maintenance vessels.

Also looking at these figures a satisfactory level of confidence can be attributed to the convergence of the obtained values, suggesting the suitability of 100 simulations in order to obtain meaningful results without exceeding with the computational time required.

4.1.4 Discussion

A case study to show the functioning of the characterisation tool, its modelling possibilities and the information obtainable in order to make decisions on the management of the offshore farm has also been presented. Despite the lack of an effective way of validating these results with an analogous existing project, this study illustrates the possible insights provided by the characterisation model. Results show the characterisation of the reliability of the devices, identifying the subsystems and components which most affect the correct operation of the turbine. This provides information on what sub-assemblies device designers and engineers should focus on, giving them the opportunity to analyse the effects of improvements in these components. For instance, the percentage contributions of each component to the total number of failures and total downtime, shown in Figures 4.7 and 4.8, can be compared also over the two maintenance vessels. The percentage contribution to the total number of failures results similar for all components in both cases. However, in the case of the HF4, the contribution to downtime of the electrical system is much higher than in the case of the Dart Fisher, at the expense of the contribution to downtime of the other components. This is due to the combined effect of the higher failure rate of this component and the higher capabilities of the HF4, which restoring this component to a functioning state more efficiently, paradoxically allows it to fail more often (in fact, also its contribution to the total number of failures in higher in the case of the HF4). This is reflected when the RPN is estimated, in Figures 4.9 and 4.10, where the distribution of the risk among components is similar with the exception of the electrical system. If variable failure rates were used, this undesirable effect may not happen as a consequence of perfect maintenance interventions.

This case study has presented forecasts on electricity production and availability of the farm as well as economic predictions in order to assess the suitability of vessel alternatives for O&M. Most of the outcomes in fact can be compared for two or more different maintenance vessels, or even a combination of them. This choice plays a pivotal role in the success of one maintenance strategy over another. Finally, considerations on the convergence of the results, due to the statistical nature of the method adopted, are taken into account to assess the consistency in the results obtained and optimise the computational time required.

Although a larger number of runs may be useful in order to ensure that more robust estimates of the KPIs are obtained, extending the simulation may result in infeasible scenarios due to time complexity. This is strongly dependent on the number of elements considered (i.e. number of devices, length of the time-series, timestep, number of access systems, number of components). For instance, for a relatively simple case study like the one considered in this section (2 devices, 14 components, 2 access systems, 10 years of MetOcean data with 3 hours timestep), approximately 2 days were required to complete the 100 runs of the simulation on a Intel i5-4200U Cpu, functioning at 1.6 GHz, with 4 GB of RAM. It is easy to speculate that guarantee statistical significance in case studies characterising modern offshore wind farms, involving hundreds of turbines and components, would be rather impractical at this stage. This, once more, highlights the need for other methodologies for the evaluation of multiple scenarios in realistic times.

As a consequence, a number of optimisation possibilities arise following the characterisation of the offshore farm. Among these, the reduction of the failure rates of the single components due to improvement in the design of the devices, the installation of redundant elements on specific components, the intensification of scheduled maintenance activities on the most sensitive components (provided that variable failure rates are used), the choice of one or more maintenance vessels which may perform better. Anyway, an iterative approach would need to be taken. Each iteration would require the lifetime of the farm to be simulated, and based on the output information one or more parameters altered accordingly, attempting to maximise the availability and electrical production of the farms while reducing downtimes and maintenance costs. Nonetheless, the optimisation process would be specific to any given ORE project, as the solution for a specific farm size and site location may not be valid or optimal for a farm of different size, device type, or resource characteristics.

4.2 Case study 2 - Verification of the characterisation model and benchmarking of the optimisation model

The previous case study has presented the implementation of the reliability-based computational model for the characterisation of the O&M procedures of marine renewables. As mentioned, in the absence of the corresponding observable system (an analogous offshore energy farm with known device information, MetOcean data and O&M strategy) the validation for this specific case study is impractical. Nevertheless, repeated simulations and analysis of the outcomes, in a sort of sensitivity study, allow the confidence in the model to increase.

Alternatively, trust can be acquired through a verification process based on other cases. This section, therefore, introduces the method used to effectively calibrate, verify and benchmark the computational tools for O&M strategies and asset management of an ORE farm, as an alternative to validation in absence of real data. The case study is used to test the quality of the results and compare them against those provided by similar tools built for the same purpose. Once that the model is verified, the evaluation functions for an optimisation of the O&M strategies described in Section 3.2.2 are then benchmarked against these outputs in order to ensure that the solutions are consistent within the overall characterisation and optimisation framework. In other words, the surrogate model is tested and refined in order to reduce the level of approximation from the characterisation model and insure that an useful accuracy is obtained. The requirements for acceptability of the models performance, as well as guidelines for further verifications using similar models, are presented. The scenario and the inputs selected for this study are introduced in Section 4.2.1. In order to follow the sequential and logical structure of this process, the input data and consequent results obtained for both processes (verification and benchmarking) are presented consecutively, together with necessary considerations, in Section 4.2.2. The main outcomes of the procedure are then discussed in Section 4.2.3.

4.2.1 Context

The drawback of using computational models for the characterisation and optimisation of the O&M strategies is linked to the difficulty in ensuring the validity of these tools, demonstrating that the system considered (the ORE farm) is being represented faithfully and adequately for the purposes of the simulation and that the model meets the specific performance requirements for which it has been built. Furthermore, operational validation of the implemented model, intended as a comparison between simulated data with data obtained by observation and measurement of the real system (Mayer & Butler, 1993), is rather impractical or extremely complex because of the scarcity of data available for real ORE projects. This in fact would require the complete and detailed knowledge of all the characteristics of the farm (devices, climate, maintenance assets) registered for a sufficient length of time (10-20 years). This difficulty is often related to both confidentiality restrictions on commercial projects and lack of experience with recently installed devices. But even if data were available, the direct comparison against system's observations alone is not enough to demonstrate the logical validity of the model's scientific content (Oreskes *et al.*, 1994), as when alternative or untested configurations are considered, the underlying assumptions may no longer be valid (Dinwoodie, 2014). In fact when validation is sought, not only the specific task the model has to carry out, as well as the success criteria to be met, have to be declared, but also the context in which the model is intended to operate (Rykiel, 1996). The model would then be declared validated for only the specific context and conditions for which it was validated. The scope for which the model can be applied will therefore expand as additional validation cases are executed.

However, there is general agreement on two aspects. First, the confidence on the outputs can be increased by gaining experience with the model, by consistently analysing the results with different case studies that cover a range of possible situations. Second, credibility in a model can be established by comparing the output data against those provided by other models, in a procedure usually denoted as *intercomparison* or *code-to-code comparison* (Dinwoodie, 2014; Dinwoodie *et al.*, 2015; Sargent, 2010). This method is commonly used in the renewable energy industry to show that different tools reach consistent results using the same input sets (Crespo *et al.*, 1988; Jonkman *et al.*, 2008; Popko *et al.*, 2012). In this case the whole process is usually referred to as verification (rather than validation) because, though the results are not directly compared against an observable system, it is ensured that the computerised model has been correctly implemented for its intended scope (Sargent, 2010). If one of the other models has been already independently validated, this process is even more worthwhile in order to show that the operating principles are consistent. However, for the reasons above, this is still not enough to guarantee full validity for all cases.

Under these circumstances, in order to increase trust and confidence in the implemented models, picking up from the development of a verification process for offshore wind O&M cost models described by Dinwoodie *et al.* (2015), a complete framework for the calibration, verification and benchmarking of computational tools in this area is presented in this section.

4.2.2 Input data and results

As mentioned above, Dinwoodie *et al.* (2015) provided a case study, including a set of suggested variations, that can be used as a reference for model developers to verify offshore wind O&M models. The base case represents a typical offshore wind farm (OWF) located in the North Sea (Fino 1, 2017), operated and maintained according to indications dictated by representative failure data of modern offshore wind turbines (Wilkinson *et al.*, 2011) and current maintenance practices using three different vessel types. Four OWF O&M models, developed by different academic and industrial institutions, have been considered for the intercomparison. This reference has been used to test, calibrate and verify the decision support model developed with the aim of characterising the maintenance activities of an offshore energy farm, as well as identify possible areas of improvements for the model.

In order to check and improve the agreement with the other models, as well as adjust the model to better represent the case study, calibration is first required. In this phase all the input data that constitute the base case scenario have been gathered, and a first set of simulations have been run in order to compare the outputs obtained with those of other models. From these, a series of key results have been selected among those available. These have been selected due to their relevance from the perspective of a decision-maker. These are the O&M costs, the availabilities of the devices, vessels and repairs costs, number of corrective events, energetic and economic losses. The variations between each of the model's outputs and the respective indicator for the other models have been analysed, and the reasons for the difference identified and corrected. The changes required during the calibration have included the introduction of new output variables or the modification of existing ones in order to agree on the terminology used by other model developers, the introduction of new conditions to trigger a certain event or variations to the existing ones, the adjustment of relationships linking two or more variables, the refinement of the criteria for the assignation of duties and available assets. After the necessary adjustments, the results shown in Figure 4.18 have been obtained. Here the range of values estimated by the other models is represented by a vertical black line, with minimum and maximum indicated by a downward and upward pointing arrows respectively and the mean by an horizontal line; a red cross is used to represent the value provided by the developed characterisation model, here indicated as UoE/JFMS. The values in the figure have been normalized with respect to the mean of the values provided by the other models. A detailed analysis of these results is presented in the following Section 4.2.3.

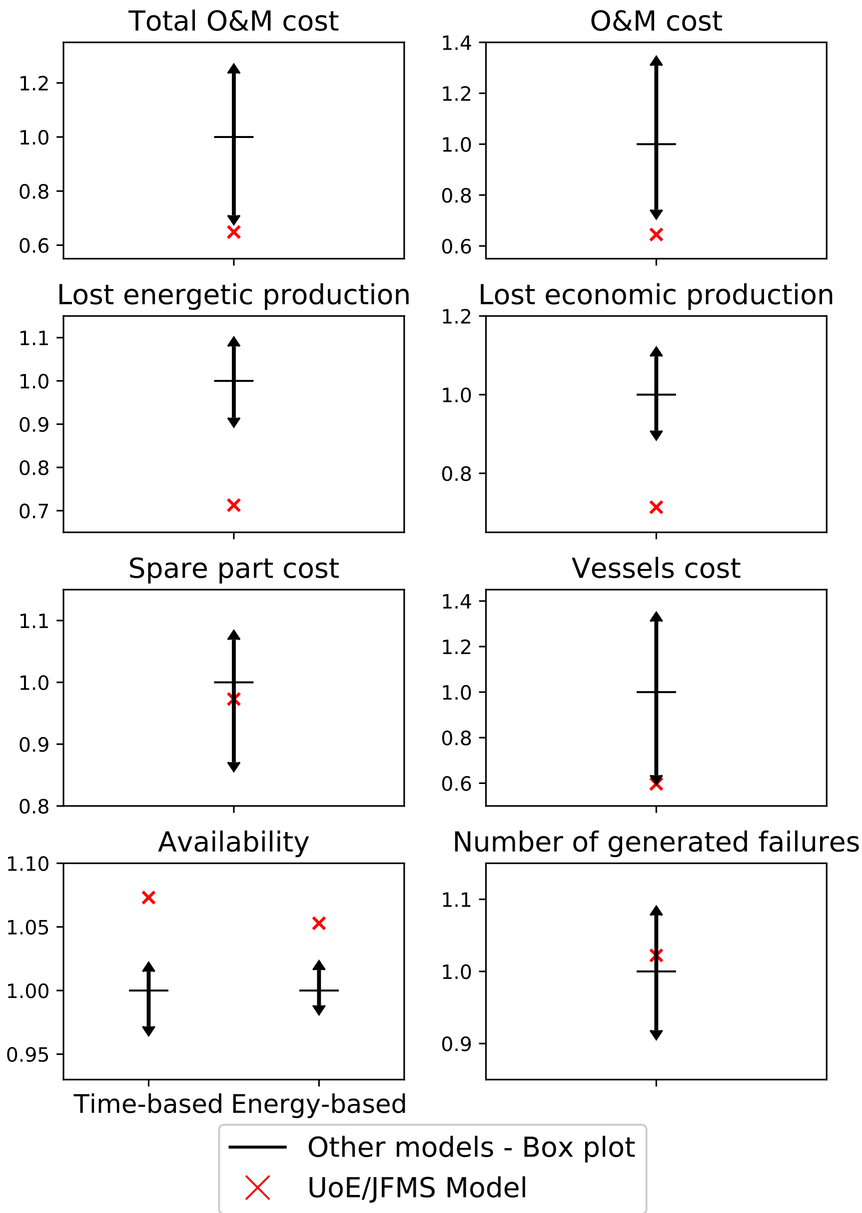

Figure 4.18: Results of the calibration for the UoE/JFMS Monte Carlo O&M tool in the base case scenario normalised to the mean obtained with the other models.

Following the calibration of the model using the base case, a set of variations to this scenario are explored in order to verify the present model. In this way, the trends across different cases can be evaluated in order to extend the model's credibility over a wider domain. This process increases the confidence and reliability of the present model while also offering insights into possible improvements. According to the indications provided in the work describing the verification of the other models (Dinwoodie *et al.*, 2015), four variations to the base case study have been prioritized. These represent high load cases for the input variables, i.e. more extreme situations to test the model's response. These are namely:

- an increase in the failure rates of the device's components;
- a reduction of the crew transfer vessels available;
- the exclusion of all failures categories (manual reset, minor repair, medium repair, major repair, yearly service) except one (major replacement); and
- the exclusion of components requiring heavy lift vessels for maintenance.

These different cases are numbered from 1 to 5 and refer to the scenarios described in Table 4.4.

Table 4.4: Description of the case studies used for the verification as suggested in Dinwoodie *et al.* (2015).

Case	Scenario	Description
1	Base case	As described in Dinwoodie *et al.* (2015)
2	Failure rate sensitivity	All failure rates (except annual service) increased by 200%
3	Fewer vessels	Number of maintenance crew transfer vessels reduced from 3 to 1
4	Single failure class	Only major replacements (all other failure rates set to 0)
5	No major repairs	Only transfer vessels in the maintenance fleet

Thus, according to these assumed variations, the simulations have been repeated after changing the initial set of inputs. It must be noticed that the case number 1, the base case, is the same used during the previous process of calibration, therefore a major correlation for this case is attributable to the tuning procedure previously operated. However, all the variations are relative to this case, and this is thus included as the starting point of the verification. Following the comparison against this set of variations, the results shown in Figure 4.19 have been achieved. The values obtained during this process, both for the base case and the successive variations, are shown in Table 4.5.

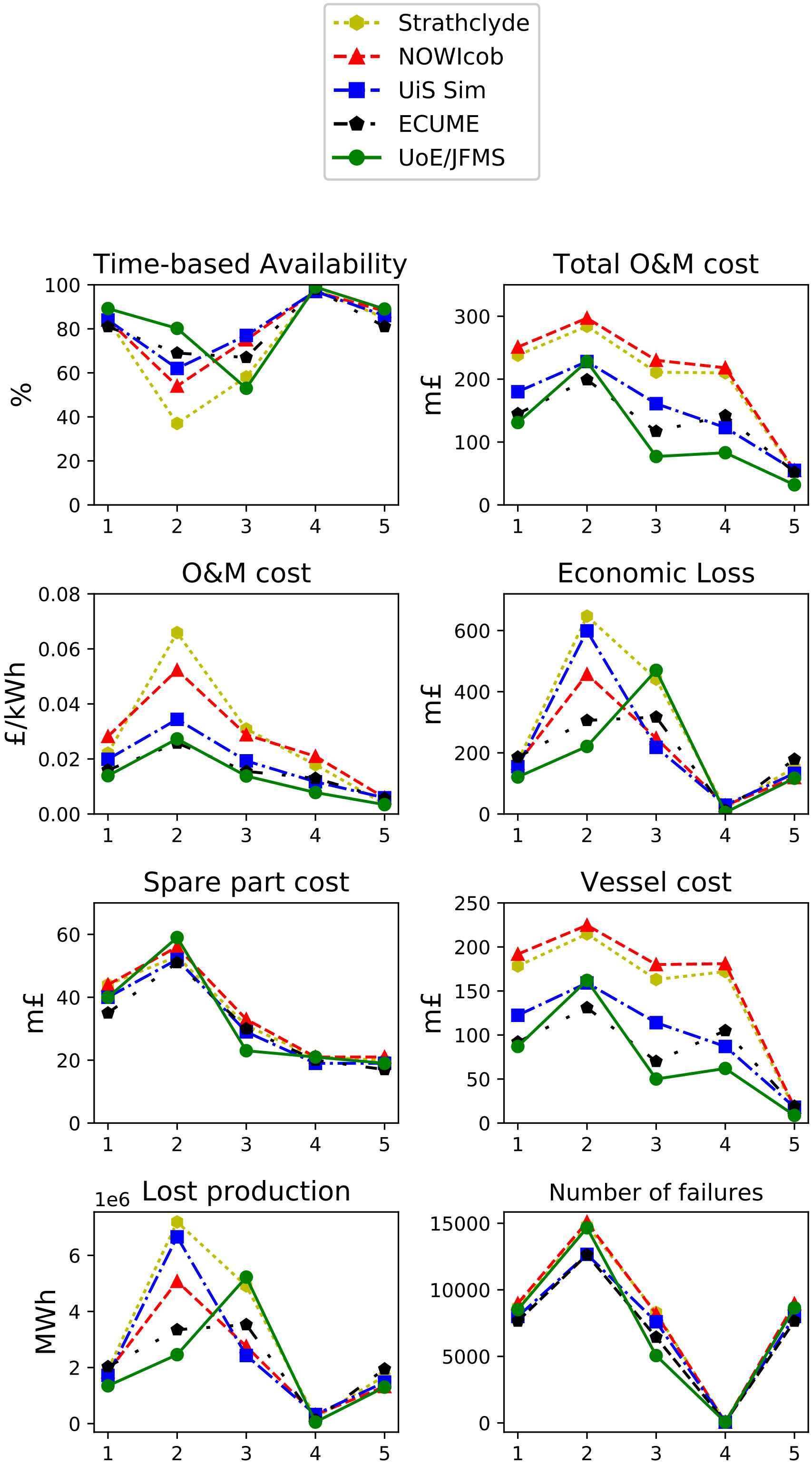

Figure 4.19: Results of the verification for the Monte Carlo tool across different scenarios.

Table 4.5: Values of the output variables compared across different scenarios for the considered models.

Total O&M cost (m£)							
Case/Model	Strathclyde	NOWIcob	UiS Sim	ECUME	Mean	UoE/JFMS	% from mean
Base case	238.32	251.68	180.29	144.77	203.76	132.15	-35.14
Failure rate sensitivity	284.32	297.62	228.71	199.40	252.51	228.86	-10.34
Fewer vessels	211.88	230.74	161.63	117.15	180.35	77.60	-132.39
Single failure class	210.37	218.40	123.40	142.11	173.57	83.73	-107.29
No major repairs and heavy vessels	53.27	55.56	55.01	52.32	54.04	32.26	-67.52

O&M cost (£/kWh)							
Case/Model	Strathclyde	NOWIcob	UiS Sim	ECUME	Mean	UoE/JFMS	% from mean
Base case	0.022	0.028	0.020	0.016	0.021	0.014	-35.33
Failure rate sensitivity	0.066	0.052	0.034	0.026	0.045	0.027	-63.23
Fewer vessels	0.031	0.029	0.019	0.015	0.024	0.014	-70.80
Single failure class	0.018	0.021	0.012	0.013	0.016	0.007	-104.62
No major repairs and heavy vessels	0.004	0.006	0.006	0.006	0.005	0.003	-56.29

Lost production (MWh)							
Case/Model	Strathclyde	NOWIcob	UiS Sim	ECUME	Mean	UoE/JFMS	% from mean
Base case	1920534	1847002	1720000	2029499	1879259	1347870	-28.28
Failure rate sensitivity	7190270	5073887	6660000	3348119	5568069	2458847	-126.45
Fewer vessels	4909324	2754752	2430000	3528888	3405741	5225384	34.82
Single failure class	213054	313717	324000	137517	247072	53784	-359.37
No major repairs and heavy vessels	1696193	1321231	1480000	1949650	1611768	1300576	-23.93

Economic loss (m£)							
Case/Model	Strathclyde	NOWIcob	UiS Sim	ECUME	Mean	UoE/JFMS	% from mean
Base case	172.85	166.35	154.80	186.43	170.107	121.31	-28.69
Failure rate sensitivity	647.12	457.16	599.40	306.39	502.51	221.30	-127.08
Fewer vessels	441.84	248.15	218.70	317.43	306.52	470.28	34.82
Single failure class	19.17	28.25	29.16	12.40	22.24	4.84	-359.56
No major repairs and heavy vessels	152.66	119.01	133.20	179.10	145.99	117.05	-24.72

Spare parts cost (m£)							
Case/Model	Strathclyde	NOWIcob	UiS Sim	ECUME	Mean	UoE/JFMS	% from mean
Base case	43.96	43.89	40.83	35.81	41.12	40.01	-2.70
Failure rate sensitivity	53.51	56.88	52.53	51.61	53.63	59.86	10.41
Fewer vessels	31.96	33.91	29.73	30.25	31.46	23.98	-31.19
Single failure class	21.68	21.14	19.30	20.78	20.72	21.02	1.43
No major repairs and heavy vessels	20.44	21.12	19.51	17.16	19.55	19.11	-2.34

Vessels cost (m£)							
Case/Model	Strathclyde	NOWIcob	UiS Sim	ECUME	Mean	UoE/JFMS	% from mean
Base case	178.36	191.79	122.43	92.97	146.38	87.37	-40.32
Failure rate sensitivity	214.82	224.74	159.15	131.79	182.62	162.58	-12.33
Fewer vessels	163.92	180.83	114.87	70.91	132.63	50.85	-160.82
Single failure class	172.70	181.27	87.08	105.34	136.59	62.33	-119.13
No major repairs and heavy vessels	16.83	18.45	18.47	19.16	18.22	8.76	-108.09

Availability (%)							
Case/Model	Strathclyde	NOWIcob	UiS Sim	ECUME	Mean	UoE/JFMS	% from mean
Base case	83.70	83.74	84.40	80.82	83.16	89.24	7.31
Failure rate sensitivity	37.09	54.67	62.7	69.67	56.03	80.23	30.16
Fewer vessels	58.13	75.79	77.9	67.81	69.91	53.08	-31.71
Single failure class	98.04	97.09	97.1	98.76	97.75	99.54	1.80
No major repairs and heavy vessels	85.76	88.53	86.8	81.55	85.66	89.65	4.45

Number of failures							
Case/Model	Strathclyde	NOWIcob	UiS Sim	ECUME	Mean	UoE/JFMS	% from mean
Base case	8693	8977	7998	7650	8330	8515	2.22
Failure rate sensitivity	14821	15096	12665	12632	13803	14659	5.84
Fewer vessels	8298	8184	7601	6439	7630	5061	-50.78
Single failure class	64	63	62	63	63	62	-2.07
No major repairs and heavy vessels	8601	8963	7999	7647	8302	8648	1.95

Once that all the information on the effectiveness of a certain combination of maintenance strategies and logistics assets for the OWF is determined, some modifications are sought in order to improve the configuration and achieve better performance (e.g. lower downtime, higher income, etc.). In order to analyse a large number of variations in a short time, removing the uncertainty related to the engineering judgement of the user and thus the possibility of neglecting improvements, the multi-objective optimisation by means of GAs approaches described in Chapters 2 and 3 have been used. Using the verified characterisation model as a reference, the second part of this work has consisted in benchmarking the evaluation functions created to evaluate the quality of a candidate solution. Hence, the three evaluation functions described in Section 3.2.2 to quantify, on a relative basis, the cost, reliability and availability for a proposed O&M strategy, are benchmarked. It has to be remembered that in this framework a candidate solution is a set of values for the decision variables of the problem, i.e. those parameters that can be varied according to the preferences of a decision-maker and therefore are not fixed due to physical characteristics of the offshore farm assets. These are:

- Number of units of each kind of vessel in the maintenance fleet;
- Ownership, overnight and seasonality properties of the maintenance vessels;
- Number of eventual redundancy measures on the components of the device;
- Number of components with immediate spare parts availability;
- Number of components with possibility of failure rate reduction due to the choice of higher quality components; and
- Number of components with possibility of overnight reparability.

As already stated, all these values can be limited by constraints in order to prevent the creation of infeasible candidate solutions according to requirements of the devices or maintenance assets.

Under these circumstances, the evaluation functions have been calibrated and benchmarked using the verified characterisation tool as the reference model. Firstly, similarly to the previous verification process, a set of reference cases has been created by changing one parameter at a time to the base case scenario. This is a modified version of the base case from the scenario simulated for the verification, with a reduced number of wind turbines (20 instead of 80) and MetOcean data (1 year instead of 10) in order to reduce the computational time required for the simulations. Each of these cases is evaluated using the same metrics (cost, reliability and availability) using both models (UoE/JFMS Monte Carlo and evaluation functions) normalized with respect to the base case. The benchmarking of the objective functions is obtained after a series of iterations in which these are progressively refined and calibrated according to the indications provided by each iteration. The changes made at each iteration consisted in:

- modify the relationships among different factors in the different contributions to the objective functions;
- introduce, reconsider or reformulate the indirect contributions to the objective functions;
- introduce or refine penalties and constraints; and
- revise availability ranges.

The considerations made during this procedure, and the actions taken as a consequence, bring forth the evaluation functions detailed in Section 3.2.2. Table 4.6 and Table 4.7 show the reduction in percentage difference between the first and last iteration for the cost and availability objective functions, including a description (in the first column) of the differences between the base case and each one of the considered case variations. It can be noticed how the difference from the reference value (assessed with the characterisation model) decreases for most cases between the first and last iteration. Though some changes led to increases, these are compensated by the overall absolute reduction. The cumulative difference decreases from 257% to 171% for the cost objective function and from 183% to 115% for the availability objective function.

Table 4.6: Cost variations from the base case for different scenarios, evaluated using the two models, between the first and last iteration during the benchmarking.

		1st Iteration		**9th Iteration**	
Case	Ch.M.	GA	Δ GA/Ch.M.	GA	Δ GA/Ch.M.
More vessels	0.01%	3.06%	3.05%	0.77%	0.76%
Less vessels	-57.03%	-89.83%	-32.80%	-89.84%	-32.80%
Vessels owned	-21.22%	-20.17%	1.04%	-23.27%	-2.05%
No vessels overnight operability	22.85%	38.18%	15.33%	36.04%	13.19%
Vessels seasonal availability	-42.61%	-55.68%	-13.07%	-36.06%	6.54%
Redundancy on components	-99.33%	-40.35%	58.58%	-88.67%	10.65%
Failure rate reduction on components	-59.20%	-29.60%	29.49%	-99.72%	-40.52%
No components overnight reparability	28.64%	31.20%	2.56%	0.00%	-28.63%
No spare parts immediate availability	0.00%	-17.30%	-17.30%	0.00%	0.00%
Vessels owned and seasonal availability	-52.93%	-68.32%	-15.39%	-48.38%	4.54%
Only one vessels, No overnight operability	-59.93%	-85.90%	-25.96%	-89.84%	-29.90%
Redundancy and failure rate reduction	-98.96%	-56.96%	41.99%	-99.94%	-0.98%

Legend: **Ch.M.** = Characterisation Model (reference), **GA** = Genetic Algorithms (Objective function), **Δ GA/Ch.M.** = Difference between value of the objective function and value of the characterisation model.

Table 4.7: Availability variations from the base case for different scenarios, evaluated using the two models, between the first and last iteration during the benchmarking.

		1st Iteration		**9th Iteration**	
Case	Ch.M.	GA	Δ GA/Ch.M.	GA	Δ GA/Ch.M.
More vessels	0.37%	6.22%	5.85%	0.04%	-0.33%
Less vessels	-16.03%	-11.99%	4.04%	-8.18%	7.85%
Vessels owned	0.00%	0.00%	0.00%	0.00%	0.00%
No vessels overnight operability	-5.27%	0.00%	5.27%	0.00%	5.27%
Vessels seasonal availability	-43.99%	-38.43%	5.57%	-41.07%	2.93%
Redundancy on components	6.40%	-40.35%	32.03%	16.43%	10.00%
Failure rate reduction on components	3.28%	28.82%	25.54%	16.43%	13.15%
No components overnight reparability	-4.68%	-19.21%	-14.54%	-16.43%	-11.75%
No spare parts immediate availability	0.00%	-28.82%	-28.82%	-32.85%	-32.85%
Vessels owned and seasonal availability	-43.99%	-45.63%	-1.64%	-41.07%	2.93%
Only one vessels, No overnight operability	-25.72%	-31.66%	-5.94%	-24.61%	1.11%
Redundancy and failure rate reduction	6.40%	60.04%	53.64%	32.85%	26.45%

Legend: **Ch.M.** = Characterisation Model (reference), **GA** = Genetic Algorithms (Objective function), **Δ GA/Ch.M.** = Difference between value of the objective function and value of the characterisation model.

The full values for the deviations from the base case scenario for costs, reliabilities and availabilities are reported in Table 4.8. The comparison on the reliability indicator is not necessary because the same formulation has been used to calculate the reliability in both the UoE/JFMS Monte Carlo model and the evaluation function; as a consequence, both models return exactly the same reliability values for all cases. In this regard, the variations in reliability for some scenarios are particularly high due to the extremely low values of reliability (on the order of 10^{-6}) for the base case.

Table 4.8: Variations from the base case for different scenarios evaluated using the two models.

	Monte Carlo			**Evaluation functions**		
Case	Cost	Reliability	Availability	Cost	Reliability	Availability
More vessels	0.01%	0.00%	0.37%	0.77%	0.00%	0.04%
Less vessels	-57.03%	0.00%	-16.03%	-89.84%	0.00%	-8.18%
Vessels owned	-21.22%	0.00%	0.00%	-23.27%	0.00%	0.00%
No vessels overnight operability	22.85%	0.00%	-5.27%	36.05%	0.00%	0.00%
Vessels seasonal availability	-42.61%	0.00%	-43.99%	-36.07%	0.00%	-41.07%
Redundancy on components	-99.33%	783.46%	6.42%	-88.67%	783.46%	16.43%
Failure rate reduction on components	-59.20%	38179.43%	3.28%	-99.73%	38179.45%	16.43%
No components overnight reparability	28.64%	0.00%	-4.68%	0.00%	0.00%	-16.43%
No spare parts immediate availability	0.00%	0.00%	0.00%	0.00%	0.00%	-32.85%
Vessels owned and seasonal availability	-52.93%	0.00%	-43.99%	-48.38%	0.00%	-41.07%
Only one vessels, No overnight operability	-59.93%	0.00%	-25.72%	-89.84%	0.00%	-24.61%
Redundancy and failure rate reduction	-98.96%	224093.41%	6.40%	-99.95%	223936.60%	32.85%

The graphical results of the comparison for costs and availabilities are shown in Figure 4.20 and Figure 4.21.

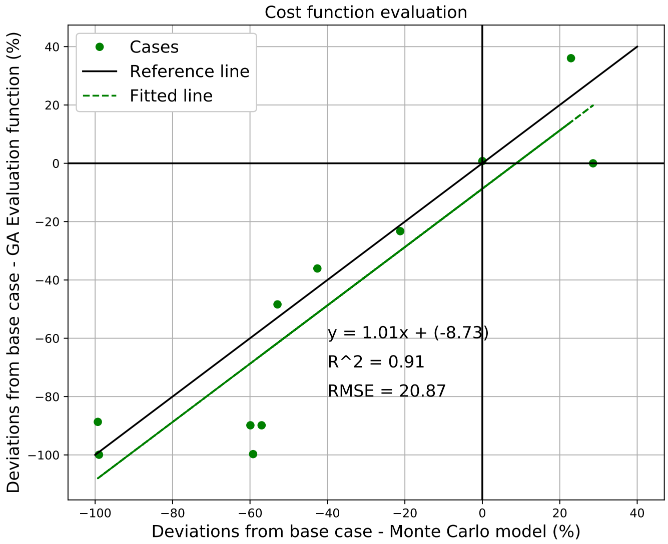

Figure 4.20: Estimated cost deviations (%) from the base case across different scenarios using the UoE/JFMS Monte Carlo model (x-axis) and the GA objective function (y-axis).

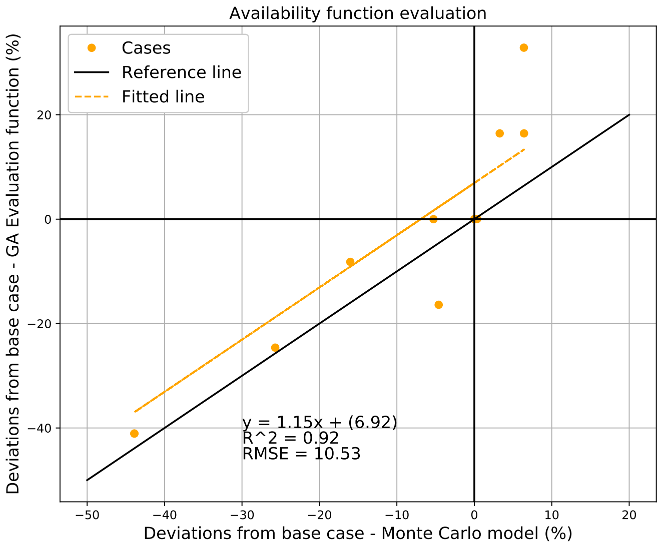

Figure 4.21: Estimated availability deviations (%) from the base case across different scenarios using the UoE/JFMS Monte Carlo model (x-axis) and the GA objective function (y-axis).

The variability of the different cases has been analysed using a linear regression approach. The equation of trend line, coefficient of determination R^2 and Root Mean Squared Error (RMSE) are displayed in each chart in order to asses the performance of the models. These allow the coefficients for the obtained trend line to be analysed, quantifying the difference between the values predicted by the UoE/JFMS Monte Carlo model and those provided by the evaluation function respectively.

But these results have been obtained by specifically altering the base case inputs set in a process similar to a one-at-a-time sensitivity analysis (although combinations of two modifications at the same time have been considered as well in order to account for eventual combined effects). Thus, as a means of obtaining further evidence of the validity of the objective function implementation and to test if the model dynamics holds, another comparison has been done. A set of cases representing the extents of the search space in the optimisation algorithm and therefore describing extreme solutions in the trade-offs between cost, reliability, and availability, have been selected for comparison. Hence, when for instance the cost/reliability balance is considered, three solutions representing low cost/low reliability, low cost high reliability and high cost/high reliability arrangements have been selected for the comparison. The other trade-offs analysed have been cost/availability and availability/reliability; analogous solutions have been chosen for these, with the exception of the availability/reliability balance where only one solution representing both high reliability and availability has been selected. These cases, together with the full results of the analysis, are reported in Table 4.9.

Table 4.9: Values for extreme solutions generated by the optimisation algorithm and evaluated using the two models.

	Monte Carlo			Evaluation functions		
Case	Cost	Reliability	Availability	Cost	Reliability	Availability
Low cost/Low reliability	8846.7	0.0092	99.25	27043	0.0092	46.68
Low cost/High reliability	8846.7	0.0152	99.33	33748	0.0152	47.84
High cost/High reliability	17063	0.0152	99.91	9773721	0.0152	61.78
Low cost/Low availability	8846.7	0.0092	99.25	27043	0.0092	46.68
Low cost/High availability	9177.7	0.0059	99.89	51298	0.0059	75.47
High cost/High availability	69909.00	0.0082	97.23	8422217	0.0082	80.52
High availability/High reliability	17027.00	0.0152	99.76	4015013	0.0152	73.52

The input variables defining the different scenarios, described in previous Section 4.2.2, have been used to run new simulations with the UoE/JFMS Monte Carlo tool, and again the results have been compared with the estimations of the evaluation functions. The outcomes of this comparison, obtained after a new series of iterations, are shown in Figure 4.22 and Figure 4.23. As already mentioned, the reliability calculation is not plotted as the same formulation is used by both the UoE/JFMS Monte Carlo tool and the evaluation function.

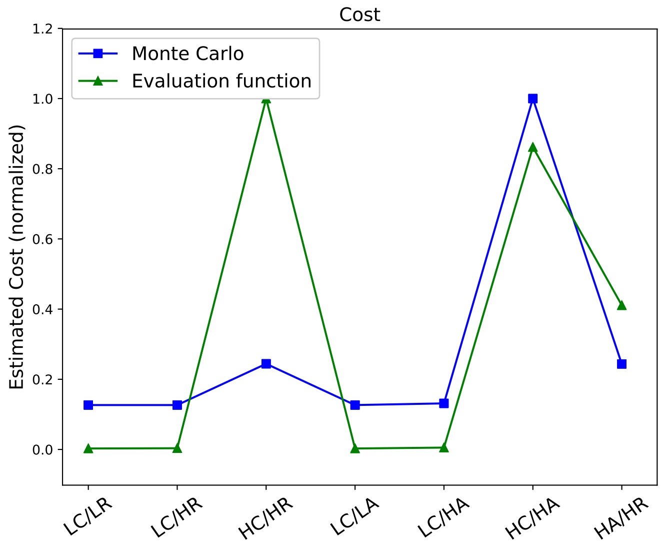

Figure 4.22: Extreme cases generated via the optimisation algorithm: comparison between the two models for the estimated cost.

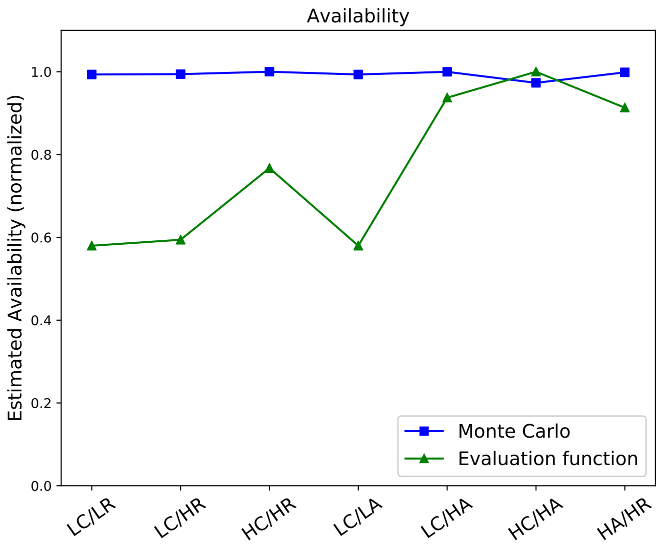

Figure 4.23: Extreme cases generated via the optimisation algorithm: comparison between the two models for the estimated availability.

4.2.3 Discussion

The results presented for the calibration of the UoE/JFMS Monte Carlo model against the base case in Figure 4.18 indicate that, within relatively acceptable limits (< 30-40%), all the selected output parameters are similar to those of the other models. Larger differences are noticed for the estimated losses and availabilities. In fact, the number of generated failures (i.e. corrective maintenance interventions) is slightly lower, partly due to the constraint that failures cannot be assigned when the device is already in downtime, which reduces maintenance expenses. But more importantly, the lost production (and as a consequence also the economic loss) is lower. A plausible explanation for this is that the simulated repairs or replacements times are lower. This argument is further supported by the moderately lower vessels cost and, consequently, a reasonably higher availability of the farm. Because of this, the overall O&M cost (intended as a sum of vessels, repairs and technicians costs) results somewhat lower than those provided by the other models, therefore including the case in which the O&M cost is normalized by the amount of electricity generated. Furthermore, crew costs, included in the calculation of the total O&M costs, result always lower because calculated according to the effective working hours rather than estimated according to the staff annual salary.

However, it has to be highlighted that the main goal of the calibration procedure is not to ensure that all the results exactly coincide quantitatively. As all the models under consideration have been validated only to a limited extent, the goal of this step has not been to exactly reproduce the results of the existing models, but to provide results consistent with these in order to increase confidence in both the implemented modelling approach and assumptions. Therefore, moderate fluctuations, particularly if supported by differences in variables adopted definition, do not affect the outcome of the comparison and can rather aid in the further development of the present model. Besides, it can be argued that models are never completely validated because it is not possible to guarantee complete agreement between the real system and the model for its entire domain of applicability and circumstances not already observed (Dinwoodie *et al.*, 2015; Sargent, 2010). Similarly, in the results of the verification process illustrated in Figure 4.19, it can be seen how though there are discrepancies for some cases, the results and trends observed are qualitatively similar for all models.

When the values in Table 4.5 are analysed, the percentage differences between the UoE/JFMS model and the mean of the other O&M models results can be important for a number of cases. However, the value of the mean is sometimes impacted by the value provided by only one of the models (the outliers), which is significantly higher or lower than those provided by the others. Therefore, for the sake of conceptual validity, it is also useful to look at the difference from the model which provided the most similar value to that estimated by the model under examination. Under these circumstances, the model tested in this work can be regarded as verified with respect to the aim and features of the original implementation, i.e. characterisation of the reliability, availability, maintainability and profitability performance parameters corresponding to a given set of possible assets and resources for an offshore wind energy farm.

When looking at the results of the benchmarking for the evaluation functions in Figure 4.20 and Figure 4.21, the differences from the reference line, which would indicate a perfect match between the variations in the UoE/JFMS Monte Carlo model and those in the objective functions, are relatively small. This is supported by the high value of R^2 and the proximity of the slope to 1, confirming a good agreement between the two models. Furthermore, the *RMSE* is around 10% and 20% for the cost and availability evaluation functions respectively, and could be further reduced by reducing the differences of the three most diverging scenarios (i.e. the points most distant from the reference line). These are the same for both figures, and represents those cases in which failure rate reductions, redundancy elements or both are introduced in the case variations. This gives useful insights towards the contributions that could be further refined in the evaluation functions.

Finally, looking at the results of the comparison with the variations derived from the optimisation algorithm, for the estimated costs in Figure 4.22 it can be seen how the values provided by the two models, differ quantitatively for the case of high cost/high reliability but follow a similar trend for all the remaining cases. It must be noticed that all values have been normalized with respect to the highest value obtained for each set due to the two models operating on different orders of magnitude, as further explained in Section 5.3.

Furthermore, changes from one case to another are more accentuated for the evaluation function than in the UoE/JFMS Monte Carlo model; this can be somehow expected since very different situations, at the extremes of optimisation search, have been picked for the comparison. The same considerations apply to the estimated availability, as shown in Figure 4.23, where this difference is even clearer, with a roughly constant value among the various scenarios for the UoE/JFMS Monte Carlo tool but more substantial variations in the evaluation function. Besides, the trends in the two models are not as similar as for the costs. By analysing the various contributions to the variation in availability for the different cases, it has been found that the factor which most influences these variations is the number of units for the access systems of the maintenance fleet. The difference in this case is that the evaluation function provides an expected value for the contribution to the total availability purely based on the number of units (the higher the better), while the UoE/JFMS Monte Carlo model calculates the availability of the farm after accounting for the downtime and the actual use of each vessel.

However, remaining aware of these limitations, and considering that the primary interest of a decision-maker will be ultimately focused on solutions that minimise the running costs (or the cost/availability ratio) of the ORE project, also the evaluation functions that will be used in the optimisation framework can be considered as calibrated for the purposes of this work. This is supported by the absolute differences of 12% for all the values involving low costs in the comparison of the estimated costs

(Figure 4.22) and of 6% for the low cost/high availability case in the comparison of the estimated availabilities (Figure 4.23).

4.3 Case study 3 - Optimisation of an ORE farm

Once the characterisation and optimisation models have been verified and benchmarked respectively, the third case study illustrates the versatility and applicability of genetic algorithms as an effective tool to optimise the O&M strategies of an offshore wind farm. The problem considers minimising the operating costs of the project while maximising both its reliability and availability. The three approaches described in Section 3.2.3 are compared in order to select one of them, seeking to identify the optimal configurations for the strategic assets. The variation of the economic performance indicators as a consequence of the optimisation procedure are then presented and discussed.

4.3.1 Scenario

Based on the selection criteria provided in Section 3.2.5, the values obtained in Table 4.10 are analysed in order to select one of the three proposed approaches for the optimisation. As a result, the following section examines an offshore wind project optimised using the weighted sum approach. In fact, even though the superposition method may be used, because the economic metric for the selected reliability range is lower than in the weighted sum approach (first line of Table 4.10) and at least comparable within the selected availability range (second line of Table 4.10), due to the significantly higher availability metric in the selected reliability range (third line of Table 4.10) the weighted sum approach is preferred. In any case, despite only one approach is selected in order to simplify the application of the proposed methodology, nothing prevents the use of all three presented methods for a more effective comparison.

The case study considers Westermost Rough Wind Farm (Westermost Rough Wind Farm, 2017), a wind farm off the east coast of the United Kingdom which began operation in 2015. This wind farm consists of 35 Siemens SWT-6.0-154 turbines each rated at 6.0 MW. The O&M port associated to this offshore wind project (OWP) is the Royal Dock Grimsby (2017) port, located approximately 40 km from the offshore wind farm (OWF), as shown in Figure 4.24.

Table 4.10: Values of solutions in the ranges selected according to the preferences of the authors for the case study.

Criterium / approach	**S**	**W**	**V**
Minimum cost in reliability range 98.15E-5 - 98.16E-5	1.41E6	4.30E6	3.80E6
Minimum cost in availability range 82.50 - 82.55	4.33E9	4.3E9	N/A*
Maximum availability in reliability range 9.6E-4 - 9.8E-4	69.70	82.42	67.10

Legend: **S** = Superposition, **W** = Weighted Sum, **V** = VEGA inspired. *Note:* * = Not present in selected range.

Despite the use of 6 MW wind turbines in the real project, in this case study the updated version of the turbine, which is now rated at 8 MW, is considered because this is more representative of future OWPs. In fact, since two phases that include the current configuration with 35 OWTs and an extension of this with an additional 45 OWTs (for a total of 80 OWTs and 640 MW) are considered, the updated version of the OWT allows for a reduced number of devices to achieve the same total installed capacity.

4.3.2 Input data

Similar to the previous case study 1, the MetOcean data needed for the calculation regarding energy produced and accessibility of the farm (wave height, wave period and wind speed) are retrieved using the numerical simulation model WAVEWATCH III (Tolman *et al.*, 2002) for the 10 year period from 1990 to 1999 with a timestep of 3 hours. The accessibility information, including weather windows and vessels transit times, are calculated for each day of the simulated lifetime using the offshore projects planning software Mermaid. A port-based O&M strategy is assumed, in which the OWF can be maintained by means of three types of generic vessels capable of minor, medium and major maintenance interventions respectively. These are indicated in this work as crew transfer vessel (CTV), field support vessel (FSV) and heavy-lift vessel (HLV). The wave limits for the repair actions of these vessels, as well as the majority of the cost data, have been extracted from the literature (Dinwoodie *et al.*, 2015; Katsouris & Savenije, 2017; Tavner, 2012). Where necessary, unknown economic values have been estimated based on industry experience and consistency with other economic values. MetOcean limits and economic values associated to the access systems and used for this

Figure 4.24: Map of Westermost Rough Wind Farm (Westermost Rough Wind Farm, 2017).

study are specified in Table 4.11. Even though only wave limits have been considered for the accessibility characterisations, wind and water current limits can be included if needed.

Table 4.11: Vessel cost parameters.

Access system	CTV	FSV	HLV
Wave limit (H_S, m)	1.5	1.5	2
Transit speed (knots)	20	12	11
Day rate (£)	1750	9500	150000
Standby day rate (£)	616	1232	2465
Mobilization cost (£)	0	0	27000
Transit fuel cost (£)	138	883	2187
Average daily crew member cost (£)	220	220	220

The components data for the devices, including failure rates and replacement costs, have been extracted from Carroll *et al.* (2016) by averaging over the values for the maintenance categories considered in the reference. Information on possible redundancies and other reliability related improvements have been assumed according to values reported in Table 4.12.

Table 4.12: Components parameters.

#	Component	Failure rate(f/yr)	Repair time(hr)	Repair cost(£)
1	Pitch system	1.076	89.0	65910
2	Generator	0.999	67.0	25973
3	Blades	0.520	31.2	18037
4	Lub system	0.471	22.0	5253
5	Electrical comp.	0.435	20.7	4550
6	Contactor	0.430	17.5	4564
7	Controls	0.428	17.5	4431
8	Safety	0.392	13.2	4306
9	Sensors	0.346	12.7	3995
10	Pumps, motors	0.346	11.0	3544
11	Hub	0.235	8.3	1126
12	Heaters/Coolers	0.213	8.0	1075
13	Yaw system	0.189	7.3	990
14	Tower/foundation	0.185	7.0	918
15	Converter	0.180	8.0	750
16	Transformer	0.065	3.6	527

Exploiting the values provided by the manufacturer for cut-in, cut-out and rated speed (Siemens, 2018), the remaining intermediate values of the OWT power curve are obtained by using the least square method as mentioned in Section 3.1.1.1. Finally, the strike price for the electricity generated by the OWF is assumed to be £155/MWh, the maximum possible for projects coming on line in 2015/2016 (Department of Energy & Climate Change, 2013).

Once this set of input data is gathered, a first simulation is run with the characterisation model in order to obtain a reference case, in which 3 CTVs, 1 FSV and 1 HLV (Dinwoodie *et al.*, 2015) are assumed in the fleet, for each one of the two phases of the OWF. Consequently, a new simulation with the input data provided by the execution of the GA is repeated. In this way, the values on the KPIs of the OWF can be compared before and after the optimisation and the differences quantified.

4.3.3 Results

This section details the results of the optimisation for the two phases, simulated considering 35 and 80 devices respectively.

4.3.3.1 Phase 1 - 35 OWTs

By running the GA using the weighted sum approach and the inputs described in the previous section, the Pareto frontiers illustrated in Figure 4.25 are obtained. From these, one solution (indicated by the data cursor) is selected among those obtained in the cost/availability chart, and decoded in terms of the corresponding O&M strategy shown in Table 4.13. The O&M strategy indicated by the optimisation algorithm in Table 4.13 is then re-evaluated using the characterisation tool, yielding the values presented in Table 4.14. As shown in Table 4.14, the selection of the optimised maintenance strategy allows for significant reductions of lost production by 74% and O&M costs by 33%. This, in turn, generates an increase in energy production and availability by 3%, with this last passing from 95.64% to 98.88%, and an increase of the generated income by almost 5%, which translates in additional £75m over the 10 years of the considered lifetime.

1

Table 4.13: Input variables according to decoded solution for phase 1.

Objective functions values	
Cost function	10.23 x 10^6
Reliability function	9.81 x 10^{-4}
Availability function	67.33
Access systems decision variables	
Use combinations of access systems:	Yes
Number of units available:	4 (CTV), 7 (FSV), 5 (HLV)
Vessel(s) purchase:	No
Overnight operability:	Yes (HLV)
Seasonality restrictions:	No (All vessels)
Device related decision variables*	
Redundancy measures on components:	4,5,6,9,12,13
Failure rate reduction on components:	1,2,4,5,6,7,9,10,11,12,13,14
Overnight operability on components:	1,2,5,8,10,12,13,16
Spares immediate availability for components:	3,4,6,7,10,11,15

**List of components:* 1 - Pitch system, 2 - Generator, 3 - Blades, 4 - Lub system, 5 - Electrical comp., 6 - Contactor, 7 - Controls, 8 - Safety, 9 - Sensors, 10 - Pumps, motors, 11 - Hub, 12 - Heaters/Coolers, 13 - Yaw system, 14 - Tower/foundation, 15 - Converter, 16 - Transformer.

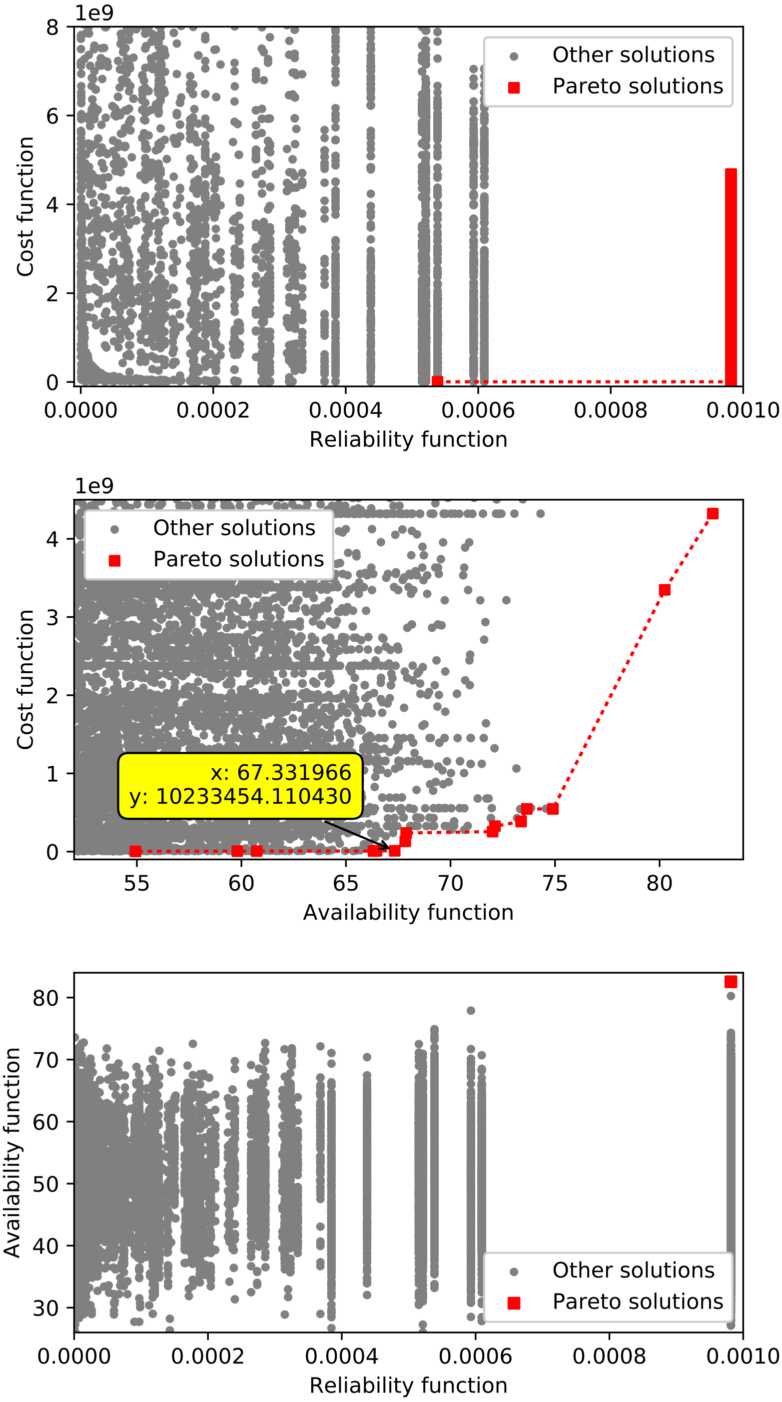

Figure 4.25: Pareto frontiers obtained for phase 1 using the weighted sum approach. Solutions plotted in terms of their cost and reliability values in Figure 4.25a, cost and availability values in Figure 4.25b and availability and reliability values in Figure 4.25c

Table 4.14: Comparison of the results obtained for phase 1 before and after the optimisation indicated by the GA.

Quantity	Value 1*	Value 2**	Variation (%)
Average annual energy (GWh)	1057.38	1093.68	3.38
Average annual loss (GWh)	48.21	12.43	-74.22
Capacity factor (%)	43.09	44.54	3.37
Equivalent hours	3776.39	3904.17	3.38
Availability (%)	95.64	98.88	3.39
Total gross production over 10 years (m£)	1638.95	1694.41	3.38
Total lost production over 10 years (m£)	74.72	19.26	-74.22
Total O&M costs - Repairs, vessels and crew (m£)	58.49	38.93	-33.44
Total generated income over 10 years (m£)	1580.45	1655.49	4.75

Note: * = Before optimisation, ** = After optimisation.

4.3.3.2 Phase 2 - 80 OWTs

The evaluation of the KPIs and the optimisation using GAs are repeated for the second phase of the case study. The Pareto frontiers obtained for this phase are shown in Figure 4.26, with the solution of interest highlighted in the same figure, corresponding O&M strategy parameters shown in Table 4.15, and the comparison of the KPIs shown in Table 4.16.

Table 4.15: Input variables according to decoded solution for phase 2.

Objective functions values	
Cost function	12.84 x 10^6
Reliability function	9.81 x 10^{-4}
Availability function	69.48
Access systems decision variables	
Use combinations of access systems:	Yes
Number of units available:	6 (CTV), 7 (FSV), 4 (HLV)
Vessel(s) purchase:	No
Overnight operability:	Yes (FSV)
Seasonality restrictions:	No (All vessels)
Device related decision variables*	
Redundancy measures on components:	4,5,6,9,12,13
Failure rate reduction on components:	1,4,5,6,9,12,13,16
Overnight operability on components:	2,3,8,10,11,12,13,16
Spares immediate availability for components:	2,3,4,5,6,7,8,9,10,12,16

**List of components:* 1 - Pitch system, 2 - Generator, 3 - Blades, 4 - Lub system, 5 - Electrical comp., 6 - Contactor, 7 - Controls, 8 - Safety, 9 - Sensors, 10 - Pumps, motors, 11 - Hub, 12 - Heaters/Coolers, 13 - Yaw system, 14 - Tower/foundation, 15 - Converter, 16 - Transformer.

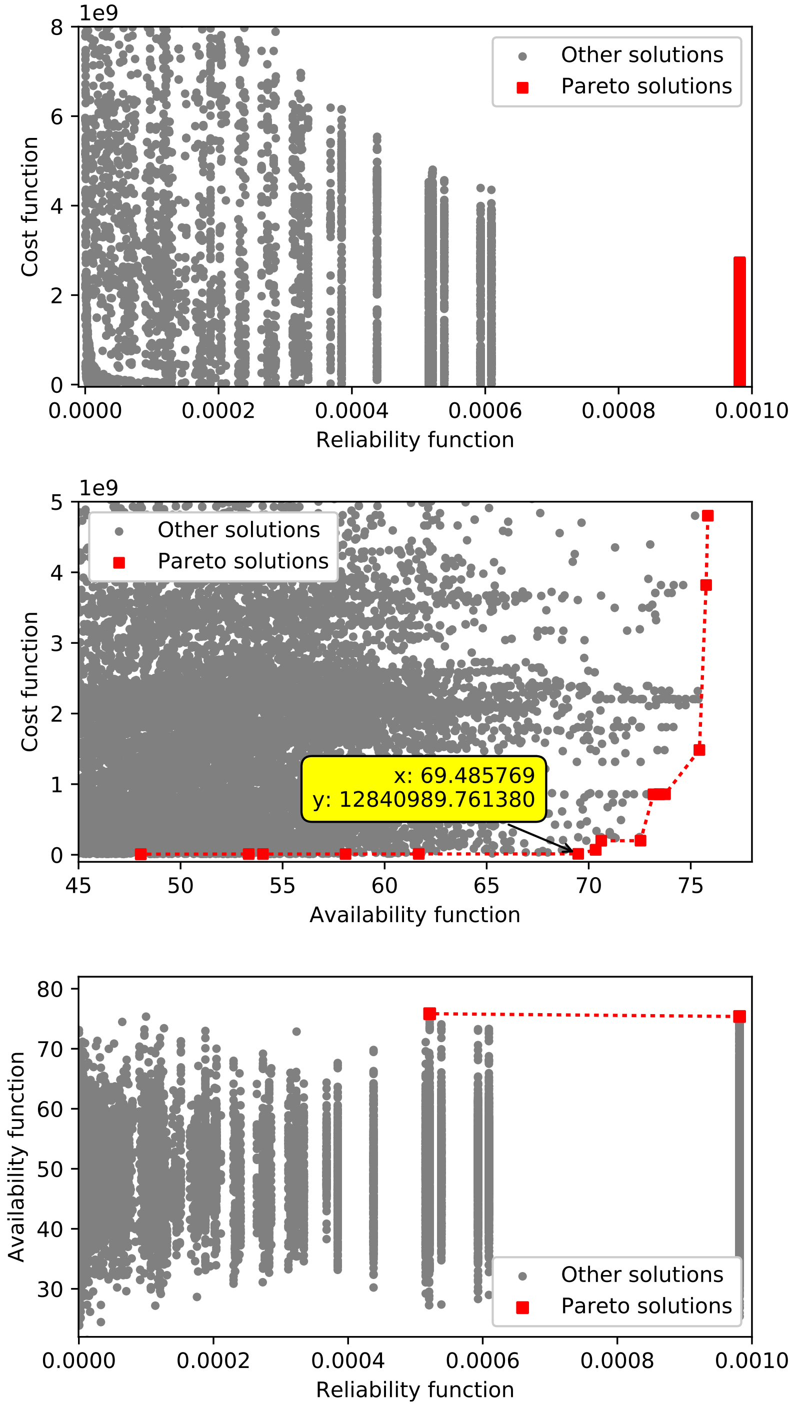

Figure 4.26: Pareto frontiers obtained for Phase 2 using the weighted sum approach. Solutions plotted in terms of their cost and reliability values in Figure 4.26a, cost and availability values in Figure 4.26b and availability and reliability values in Figure 4.26c

Table 4.16: Comparison of the results obtained for phase 2 before and after the optimisation indicated by the GA.

Quantity	Value 1*	Value 2**	Variation (%)
Average annual energy (GWh)	1757.11	2497.04	42.11
Average annual loss (GWh)	769.97	30.03	-96.10
Capacity factor (%)	31.32	44.51	42.11
Equivalent hours	2745.48	3901.63	42.11
Availability (%)	69.53	98.81	42.11
Total gross production over 10 years (m£)	2723.52	3870.42	42.11
Total lost production over 10 years (m£)	1193.45	46.558	-96.10
Total O&M costs - Repairs, vessels and crew (m£)	102.21	103.99	1.74
Total generated income over 10 years (m£)	2621.30	3766.43	43.69

Note: * = Before optimisation, ** = After optimisation.

Similar to the previous situation, also for the second simulated phase the optimised O&M strategy allows for the achievement of reduced losses and increased production, as shown in Table 4.16. In this case, the relative variations are more significant than in the first phase, with the availability increasing from around 70% to more than 98% and the capacity factor rising from 31% to 44%. As a consequence, the total lost production lowers to £46m over the 10 years lifetime, and the generated income increases by almost 44%, meaning an average additional gain of £114m per year. However, the O&M cost slightly increase (by less than 2%) compared to the base case scenario.

4.3.4 Discussion

From the execution of the GAs, a series of candidate solutions, representing a set of input data for the characterisation tool, are obtained. Due to the difficulty in interpreting the results and choosing useful candidates when these solutions are plotted in terms of the three objective functions considered (cost, reliability and availability) simultaneously (e.g. in a 3D scatter diagram), the charts providing a visual representation of the solutions (and associated Pareto fronts) in terms of two objective functions at a time are preferred. For this case study, the profitability of the project is prioritised. As a consequence, decisions are principally based on the cost/availability chart because these two criteria are more relevant from a profitability perspective. This is a preference of the author in order to illustrate the case study, but any decision-maker could use other criteria according to his/her priorities. Nevertheless, the associated value for the third objective function, the reliability, can be used in order to refine the choice between two or more neighbour solutions in the Pareto frontiers.

In the charts where the reliability is considered, a discretisation of the solutions can be observed due to the constraints which allow only certain combinations of redundancy and failure rate reductions for the components of the device. The cost/availability charts, however, appear continuous in the objective space resulting in a more well defined Pareto front. As the two phases considered in this case study differ only in the number of turbines, with all other parameters held constant, a similar distribution of solutions can be observed in the presented Pareto fronts. The criteria used for the selection of the optimised solution in both charts looked at obtaining an as high as possible value of availability while keeping the value of the cost function as low as possible. Therefore the solutions are selected from the lower right portion of the charts, prior to the cost function rising steeply. This prioritizes the cost variation eliminating excessively high cost solutions (especially after taking into account the large variations of the cost function on the y-axis).

Even though the resulting distribution of candidate solutions (and as a consequence the choice of the optimised solution) is similar for both the phases of the OWF, the selected optimal O&M strategies to be tested with the characterisation tool differ due to the increased number of turbines in Phase 2. As a result of the increase in the turbines of the OWF, the number of maintenance interventions increases and the costs dynamic changes. As a consequence, a larger fleet is required and it is necessary to select a number of access systems more appropriate for the number of repairable components which can be repaired by that type of vessel. Similarly, while the full availability without seasonal restrictions is required in both cases, the overnight operability is necessary only for major interventions with the HLV in the first phase, whereas for the second phase it is needed also for minor operations with the CTVs.

Turning to the component specific decision variables, thanks to the higher number of vessels available less components with lower failure rate and repairable or replaceable overnight are required to achieve the desired values in the second case. On the other hand, due to the increased number of devices, a greater number of components require the immediate availability of spare parts when compared to phase 1. In addition, in order to cope with the higher number of repairs, more maintenance interventions are needed. This increases the direct O&M costs, causing also a raise in the optimised strategy with respect to the base case scenario due to the higher number of vessels required, but which is still highly compensated by the reduced downtime production.

Of course, these choices and improvements on the devices have a cost due to the installation of more expensive components, redundant elements and spare parts, but also to higher vessel charters, crew compensations and port expenses. These additional expenses are calculated using the same formulation of the optimisation framework, and their value estimated around the 13% and 8% of the final O&M costs respectively for the 2 simulated phases. Even if these values are rough approximations, the additional expenses are highly compensated by the significant increases in energy production and final generated income, as shown in Tables 4.14 and 4.16. The introduced improvements result in a significant reduction of the energy losses due to downtime and of the O&M costs due to repairs and replacements and use of vessel. This, in turn, increases the availability and profitability of the OWP for both the simulated phases, reaching considerably high availability value with respect to those of typical OWFs. Firstly, these variations depend on the reference case, based on the literature, selected for this work, and could vary accordingly if other options are considered. Secondly, this gain is also due to the relatively high Contract for Difference (CfD) assumed for this project. Lower CfDs would result in less effective improvements, as well as potentially generate very different strategies during the search for optimised solutions and orientate the selection according to different criteria (e.g. lower costs rather than higher availability). However, reasonable improvements can be expected also with lower CfDs or other compensation schemes. For instance, with a CfD price of £57.50/MWh according to the last CfD auction for OWPs scheduled for commissioning in 2022/23 Contracts for Difference news (2017), the generated income over the 10 years of simulated lifetime would lower to £589m and £1331m for the first and second phase respectively, leaving a reasonable margin of profit even after deducting the additional expenses due to improvements. If all the data for the eventual introduction of improvements are available, the minimum CfD or other mechanisms needed in order to guarantee the profitability of a project can be established.

This effect is more observable for the second phase of the wind farm where, although the optimisation process results in a marginal availability increase, the impact on production and revenue is significant. In the first phase of the wind farm, however, a more significant impact on the availability as a result of the optimisation process is observed. This is in part due to the modest results obtained before the optimisation, when the base input set is less suitable because of the high number of wind turbines. This reflects the major difficulty in managing the maintenance assets when the number of devices to operate and maintain increases, but also shows the increased importance of using optimisation models for larger OWFs.

As introduced in Section 3.2.2.3, a major limitation of the availability objective function is in the contribution related to the failure rate reduction. This is due to the inability in effectively distinguish between components (i.e. the same failure rate reduction on the gearbox or on a small sensor would have the same effect on the calculation of this contribution). This leads to possible uncertainties, which are difficult to quantify, in the calculation of the overall availability function and, as a consequence, also on the indirect contributions to the cost function related to the availability variations.

It is not simple to assess whether the solutions suggested by the optimisation tool could have been found using just engineering judgement and knowledge of the farm, as well as if similar or better solutions could have been found using other approaches. In fact, some choices, like for instance that of allowing overnight operability of the vessels, are more intuitive than others, like for example the exact number of access systems or the components on which apply redundancy measures. Nevertheless, when the values suggested by the optimisation algorithms are analysed, these results appear reasonable and conform to expectations in sight of the kind of ORE farm and devices that have to be operated and maintained.

Chapter 5

Discussion

Contents

Although a brief discussion of the results is provided at the end of each case study, this chapter summarizes and discusses the implications of all the case studies and how these relate to one another. This then leads to the principal contributions of the thesis. In addition, considerations of the overall framework and its relationship to the research questions identified at the beginning of this work are included.

5.1 Characterisation model

In the first part of this work, after reviewing the approaches and methodologies available in this area, a characterisation model based on Monte Carlo simulation has been identified as the most suitable approach to provide accurate estimates on the operational aspects of an offshore farm. The Monte Carlo method is suitable here due in part to the ease with which it can be implemented and in part due to its ability to incorporate the stochastic nature of the failure of a device. To be more specific, this is achieved through the identification of the high level production drivers, as well as the delivery of important early insights, in particular into yield (and thus revenue), availability and reliability of the farm. The focus in this phase is to establish the key O&M and cost drivers among the input factors: harbour location, vessels type and numbers, helicopter option, crew size and spares supplies to mention a few. Accordingly, eventual weaknesses of the assets and possible areas of improvement are identified.

This model, and as a consequence the overall framework, has been developed in such a way to be directly applicable in multiple sectors (offshore wind, wave and tidal energy). This permits to show the direct extendibility of the implemented methodology to different technologies. Taking this into account since the beginning of the development permitted to achieve a high level of flexibility without trading off accuracy.

As shown in the case study in Section 4.1, two similar maintenance system can be compared to assess which one is more effective in providing the maintenance activities and especially increasing the devices' availability during periods of higher resource, in order to maximise the profitability of the farm. Although the choice of a more capable or more efficient access system may seem obvious, with this kind of modelling it is possible to assess and quantify the advantages of a choice over another, and as a consequence weigh them against eventual additional costs and disadvantages. Similarly, despite possessing the failure data of the devices can give an idea of the reliability of the ORE farm, simulating the faults and repairs provides a thorough understanding of the effects and significance of these events. In other words, the relationships among the available resource, maintenance schedules and generated electricity are evaluated, and the effects of different choices in terms of maintenance assets are efficaciously grasped and measured. Despite it has not been made explicit in the case study, there is no reason way the Balance of Plant (i.e. all the structure and facilities, other than the devices, which support the delivery of electrical energy) cannot be included in this characterisation. The same reasoning may apply to other elements of the device, e.g. floating platforms.

However, as mentioned in Section 4.1.4, with this model alone the optimisation of the maintenance procedures of the farm relies on subjective analysis of the results and manual proposal of alternatives. This is accomplished by adequately (under the necessary engineering and economic constraints) varying the specific properties and values of the key cost drivers identified during the first phase of the modelling. In this way, a number of different options in terms of maintenance possibilities are generated, with associated effects on reliability, availability, energy production, revenues and costs. Consequently, comparing the different options, it is possible to assess the relative impact of each of the parameters. From this knowledge, future simulations and project decisions can be made by either including or discarding these parameters. This whole procedure can then be repeated as many times as needed in an iterative analysis, until a desired target (e.g. maximisation of the annual income) is reached.

Being based to some extent on sensitivity analysis, this process can be tedious and time-consuming, and does not ensure that the optimal result is attained. A full sensitivity analysis would provide a means to compute the variance of the results obtained as a function of variations in the input set. Despite the setting of a specific framework would be required in order to adopt such approach for different cases, a number of major factors that have a higher impact on cost and productivity of the farm have been identified. These include, but are not limited to: failure rates, vessels' capabilities, charter strategies, spare parts availability and costs.

An alternative, in order to reduce the number of options to be simulated and obtain indications on the mutual correlations between the considered variables, is multivariate analysis based on principal component analysis (PCA). This can be used in order to acquire a clearer overview of the farms dynamics and, as a consequence, discover possible patterns that can help in achieving the objectives of the decision-maker and the requirements of the ORE farm. Multivariate analysis is generally used to gain a deeper understanding of complex data sets, by simultaneously examining the mutual correlations between several variables at a time, and permitting the identification of underlying patterns and the understanding of their relevance to the problem. Within this class of methods, PCA can be used to analyse the set of data produced during the simulation, with the aim of finding attributes and trends that might have been hidden at a first analysis of the output variables.

The main advantage of PCA consists in preserving as much information as possible in a data set composed by a large number of interdependent variables, while reducing its dimensionality for an easier investigation. This is achieved by generating a new set of variables, called *principal components*, which are a linear combination of the original variables. The principal components are not directly correlated, but are generated in order to retain most of the variation existing in the original variables. Thus, although the complete set of principal components can be as large as the original set of examined variables, usually the first two principal components contain the great majority (more than 80%) of the total variance of the original data set, therefore accounting for most of its variability and mutual correlations. Hence, this technique allows for the reduction of the dimensionality of the problem while retaining the information related to trends and variations of the inter-related variables. In this way it is possible to examine the results obtained in a simpler way, in terms of fewer variables, obtaining more insights in the causes that generated the original data set and discovering tendencies that were harder to find before of the transformation.

An example of application of the PCA to the multivariate analysis of the reliability, availability and maintainability characterisations of a wave energy converters farm is illustrated in Appendix A.

Finally, in reference to the characterisation model, the introduction of new features and options or the inclusion of further inputs, mechanisms and constraints, not only on the modelling of the sub-assemblies of the devices and on the access systems but also on their mutual interaction, will allow the generation of new outcomes. These will permit a more exhaustive characterisation of the management procedures of the farm and, as a consequence, more possibilities of optimisation of the same. This aspect is further discussed in Section 6.2.1. On the other hand, improvement on the software itself will reduce the simulation time, which currently is one of the main limitations of the model. Besides, software modifications will strengthen the reliability of the method and, more in general, improve the user experience and facilitate the elaboration of the results.

5.2 Verification and benchmarking

Following the development of the characterisation model, and prior to the implementation of the optimisation framework, two main issues arise. The first relates to concerns in the reliability of the implemented Monte Carlo model and the difficulties (e.g. lack of relevant data) in validating this model. The second is the difficulty in developing a system of links and relationships (the objective functions) that can be trusted in order to implement the optimisation tool (i.e. a surrogate model) and are actually representative of the investigated problem, able to interpret the differences between decision variables and grasp the dynamics of the offshore farm as the characterisation model would. As anticipated in Chapter 2, the ideal situation in which the characterisation and optimisation tool are fully coupled is currently excluded due to the computational limitations of the characterisation approach, and simpler and faster evaluation functions are therefore required.

For these reasons, a significant part of the work consisted in verifying the characterisation model according to the considerations and guidelines dictated by Dinwoodie *et al.* (2015) for models of this type, and then, once confidence in the characterisation model has been obtained, this has been used as a reference in order to benchmark the evaluation functions developed to evaluate the fitness of the solutions in the optimisation model. The aims of these processes are twofold. Firstly, to identify and describe the steps needed to gain credibility for the O&M characterisation and optimisation models, i.e. achieve a sufficient degree of belief in their validity to justify their use for research and decision making. Secondly, to provide a reference for future modellers who want to conceptually validate a similar coupled approach when no sufficient real operational data are available.

As a consequence, the Monte Carlo model, which has been developed for the accurate prediction of performance indicators of the offshore wind project is compared with similar tools in the same area. The objective at this stage is not to obtain the most accurate outputs, nor to precisely replicate the outcomes of existing models, but to validate the robustness of the modelling approach and assumptions by exploring the qualitative coherence between models and at the consistency across different scenarios.

Once the characterisation model is verified, the objective functions, forming part of the overall framework that uses GAs for the automated optimisation of the OWF assets, are benchmarked using the UoE/JFMS Monte Carlo model as the reference for correctness of the output data. The target as part of this benchmarking is for the evaluation functions to resemble as closely as possible the results of the UoE/JFMS Monte Carlo model, thereby calibrating the evaluation functions using the outcomes of the comparison against the UoE/JFMS Monte Carlo tool. The benchmarking of the evaluation functions is subdivided in two phases: in the first one, specific calibration cases are manually created then tested with both models (UoE/JFMS Monte Carlo and evaluation functions), while in the second phase, a wider search procedure is used to identify the verification cases. The scenarios analysed in this second part of the benchmarking, in Section 4.2.2, are deliberately extremely different in terms of outcomes produced, which make the desired match between models more challenging.

The overall analysis shows good agreement between the results provided by the implemented characterisation tool and those given by other models built for similar purposes, as well as consistency between the characterisation and optimisation frameworks. Specific measures for the evaluation of the credibility of the models are provided, and eventual discrepancies are quantified and explained.

Both models undergo an iterative tuning and adjustment process. Through this the UoE/JFMS Monte Carlo tool is modified during each iteration of the calibration depending on the differences with the other models; similarly, the evaluation functions are refined during each iteration of both phases of the benchmarking (firstly when solutions from the UoE/JFMS Monte Carlo tool are tested with the evaluation functions and secondly when extreme solutions from the the optimization algorithm are run with the UoE/JFMS Monte Carlo tool) depending again on the results of the comparison. The number of iterations is not fixed, and it is determined by the judgement of the developers in determining when the results are sufficiently satisfactory. However, for a truly effective verification, the evaluation functions shall not be further tuned when the results are compared for different cases. For this purpose, the model will have to be tested for a wider range of situations.

This verification and benchmarking method therefore provides an awareness of the capabilities and limitations of the implemented models, making it easier to distinguish between the differences in assumptions or modelling approaches as well as those due to actual implementations errors. In this way tools are refined and improved, further understanding of the mechanisms leading to an outputs set is acquired and experience in interpreting the results is gained. On the other hand, awareness of the limitations of a verification process compared to a validation against a real system for an extensive set of situations must be kept in mind at all times, both during the verification of the Monte Carlo model against other O&M models and during the benchmarking of other tools using as a reference a previously verified (but not validated) model. Validation against an observable system, as well as repetitive use of the tools, are still needed in order to further calibrate the models and be sure that all the variables playing a role in the management of the ORE farm are being considered.

Finally, it must be remembered that the implementation of the evaluation functions in the GA is established as a substitute solution in order to avoid the usage of the UoE/JFMS Monte Carlo tool at each run of the optimization, due to the significant computational time required by this last for some cases (long MetOcean series, a large number of wind turbines, extensive list of components, etc.). However, a preliminary estimation with the Monte Carlo tool is required in order to get an understanding of the farm and some of the inputs for the optimisation model. Besides, this remains the preferred solutions if computational and time constraints are satisfied.

To conclude, while long-term operability data of offshore energy farms remain unavailable, trust and confidence in simulation models for the logistics management of offshore energy farms can be acquired via verification across different base cases, including a series of extreme variations, for very different contexts and using other models as a reference.

5.3 Optimisation model

Once that appropriate evaluation functions are determined following the benchmark with the characterisation model, an optimisation framework based on GAs is implemented. In this way, a novel approach utilising genetic algorithms is used for the optimisation of the maintenance assets of an offshore wind farm. Three methods are proposed for the automated evolution of the candidate solutions towards the most desirable combinations of decision variables and according to multiple objectives. The algorithms are coded in Python 2.7 for easy programming, open access, computational speed and future possibilities of parallel computing and integration with other parts (e.g. the Monte Carlo tool). The development of this model positively answers to the question of whether the best logistics and maintenance assets can be established in an ingenious and reliable way, able to effectively include engineering requirement and financial constraints, and not necessarily subject to the experience and judgement of a decision-maker. In this way, several strategies can be evaluated in a shorter time, and innovative O&M solution, with respect to classical or ordinary solutions for the same farm, can be possibly found. However, it must be remembered that this effectively constitutes a surrogate model, which does not capture directly the underlying physics of a system (i.e. the ORE farm), like the implemented characterisation tool.

Instead, this metamodel tries to statistically perform the necessary measurements in the same way the model that it is substituting would. This means that despite there is a correlation between the two models, reinforced by the calibration and benchmarking process described in Section 4.2.2, there are still differences between the results given by the characterisation model and those given by the GAs for the same case or variation, as well as a further level of abstraction between the surrogate model and the real world. In addition, the effects of scheduled and predictive maintenance interventions are not explicitly included, which limits the use of the surrogate model as a complete alternative to O&M characterisation tools.

Despite the vast assortment of available possibilities, the selection, crossover and mutation mechanisms in the GAs, described in Section 3.2.3, have been initially selected for their ease of implementation compared to other alternatives. Nonetheless, considering the effectiveness in both the exploration and exploitation of the search space, and the achievements of promising results, it has been decided to continue with the same mechanisms. This choice is justified by the fact that GAs are generally very problem specific, and before any knowledge of the problem all mechanisms are equally valid as starting points. This does not preclude the possibility to implement different mechanisms in order to compare them, remove any weakness and select the most effective for the optimisation of the O&M assets. For instance the single point crossover selected in this work has the disadvantage of being potentially destructive of good solutions, because it causes a major change in the structure of the chromosome that forces large shifts in the objective space. This, in turn, might lead to a quick (premature) convergence of the best solutions, as could be the case in the example in Figure 3.15, with the consequent possible exclusion of valid solutions.

The selection of the most appropriate approach may be case-specific, and in some cases even a combination of them might be beneficial in order to obtain better solutions according to the priorities of the decision-maker. For this reason, if there are not computational nor time constraint, for a wider exploration of possible solutions it is convenient to run all the approaches independently from the case study considered. In this regard it is worth mentioning that the computational speed of the implemented GA approaches is able to provide a range of non-dominated solutions in a matter of seconds or at most minutes. This is a huge advantage compared to the time complexity of the characterisation tool discussed in Section 4.1.4. This can be exploited also in cases like the one presented in Section 4.3, where two phases with different number of devices are analysed for the same ORE project. Despite the same strategy obtained with the phase 1 could be tested with the phase 2 and the limitations of having a higher number of devices measured, the very limited computational effort makes more convenient to run again the optimisation algorithm for the extension.

Even though all three approaches combine the results of different runs, and some computational time is therefore spent exploring areas of the search space that may be uninteresting to a decision-maker, this does not delay the simulations excessively. On the other hand, this permits to obtain a clearer image of the explored space and the presence of more solutions on the Pareto front.

On a similar note, a more thorough comparison of the GA methodologies should compare their computational complexity as each of the methods does not intrinsically require the same number of evaluations. Although the parameters of the GA (number of generations, number of individuals, etc.) do not vary, the final solutions are obtained by letting random individuals evolve according to different evolutionary paths in each approach and then analysing the aggregated results. In this work, the conditions for each path are dictated by the objective functions in the superposition approach proposed, the values of the weights at each iteration in the weighted sum approach and the selection criteria in the VEGA inspired approach. As a result, an uneven number of final solutions may be obtained for each approach if the parameters are not properly tuned, and consequently the three approaches might be unfairly compared. For example, the total number of possible solutions analysed in the superposition approach is given by the number of individuals in a population multiplied by the number of generations. But in the weighted sum approach the result of this product has to be multiplied also by the number of iterations over different weights; as a consequence the total number of candidate solutions is much higher, and possibly the explored search space wider, with this second approach.

Though the methodology aims to automate part of the decision making process, the final decisions from the Pareto front still require the interpretation of the optimisation results and some engineering judgment. This is especially true when discerning between similar solutions. For instance, following the optimisation procedure, all the improvements have to be compared against the direct costs of their implementation in order to also consider the drawbacks of a solution. As a consequence, if the characterisation model is used to verify the effectiveness of the modifications suggested by the optimisation model, the characterisation model should be modified in such a way to be capable to measure those additional capital or development expenses.

In addition, extra care should be applied in discerning in a coherent way direct costs, intended as outlays by the operator, and indirect costs, intended as the monetary value of lost production. Despite these contributions have been coupled in the objective functions, for some scenarios this may lead to an unnecessary coupling of the objectives (e.g. an increase in reliability directly causes a decrease in the costs or an increase in the availability). Possibly, if direct and indirect contributions would be kept separated, or only direct effects considered, this risk would be reduced and the use of penalties may be avoided. However, the calibration and benchmarking processes have demonstrated that both contributions must be considered to adequately represent the Monte Carlo tool. At various stages during this process it has been noticed that the exclusion of the indirect effects would significantly reduce the consistency between the approaches.

Similarly, reliability and availability look often correlated (i.e. the maximisation of one leads or is linked to the maximisation of the other). This observation makes sense also from a practical point of view, since a reliable device is usually characterised by high availability. Therefore these objective functions might be coupled in order to simplify the problem. However, the opposite is not always true (an available device may or may not be very reliable), and, strictly from an optimisation perspective, compromise solutions between these two objectives may be highly valuable. For these reasons, even though they do not always necessarily compete, reliability and availability are included as two separate evaluation functions.

As anticipated in Section 3.2.2.5, the results at the end of each optimisation are provided as unitless, in order to be considered exclusively on a relative basis for the comparison with one another rather than as a performance indicator. This choice is also due to the order of magnitude considered, especially for the cost function, which does not provide realistic values when compared with usual O&M values. However, this is due to the way the surrogate model has been structured, in such a way that the cost are not treated in an objective way (e.g. as a product between the number of units of a certain item and the cost of the single unit for the same item). Instead, the costs are calculated in such a way to magnify the difference between different solution. In other words, for optimisation purposes, the metamodel exaggerates some of the differences between solutions, and therefore it operates on different scales. The alternative would consist in normalising the values, but this would make them more difficult to be read and discerned on a plot. Nonetheless, confidence on the results should not be lost due the fact that values are not treated in an absolute way; if subjected to dimensional analysis, it would be confirmed that the value of the cost function is in monetary units and as a percentage for the availability.

The impact of the different scales used can be observed also in Figure 3.23. Here, as soon as any degree of cost is included, this dominates the search because of the major impact on the search. This is something to be aware of when using the weighted sum approach.

5.4 Common challenges

Following the discussion of the individual aspects of this work, a number of further challenges common to the overall approach can be identified.

Firstly, although it was not the subject of an active investigation in this work, the current limited availability of input data, as well as the related halo of uncertainty, is still one of the biggest challenges in the characterisation and improvement of the ORE project. This is particularly important for the reliability data, but large uncertainties and limitations (e.g. restriction due to commercial sensitiveness, doubts related to the intellectual property, approximate or inappropriate estimates, prediction models idealisations) remain also in vessels data, power characteristics, balance of plant, etc. More physical testing, detailed track records and improved modelling techniques may solve these issues, but it remains a significant criticality at the moment. As a consequence, once that results are obtained the sensitivities to each factor must be explored, and critical drivers identified especially in relationship to how these relate to one another.

Computational complexity is another common issue that has been treated throughout this thesis, due to the important influence this has in determining feasible and infeasible approaches. In particular, it has been shown how this was a major factor that led to the decision of creating a surrogate model, by means of specific objective functions, and how it influences different methods in different ways. This directly relates also to the choice of the programming language, that sometimes can make the difference in the elaboration of a code. Despite convergence towards a specific language is not essential, because some languages may be more suitable than others to a specific method, this would be desirable if two or more models have to be directly coupled.

Validation against observable systems is another topic that has been widely treated in this work, together with related challenges and alternatives. Despite the secondary options proposed, validation remains the most valid procedure to gain confidence in all the models implemented and receive useful feedback for their improvement. In this regard, it is important that calibration, verification, and validation are done with different, independent, data sources in order to ensure that every process is done rigorously and it is not influenced by external factors that may diminish its validity.

Unfortunately, the lack of data again prevents the use of validation as an immediate choice, limiting the applicability of developed models. This directly relates to another issue, which is the limited use of tools like the ones described in this work, and indirectly to a conflict of perspectives between academia and industry. The former in fact pushes for the development of new approaches and methodologies, as well as the refinement of the existing ones, whereas the latter strongly demand for an immediate application of simple existing tools in order to obtain tangible results as soon as possible. As a consequence, a need to increase the current applicability of computational models for the assets management of an ORE farm, as opposed to the continued development of new ones, is identified as a major area of improvement.

Finally, the adaptability and flexibility of these models is another possible cause of concern. This is important in the offshore wind sector, where farms with an increased number of turbines are laying the base for new maintenance strategies using innovative access systems, but even more relevant for tidal and especially wave energy converters where the lack of convergence on a specific design for the device leads to the necessity of extremely tailored maintenance solutions.

5.5 Tools coupling

When both the characterisation and optimisation model are considered together as part of an individual framework for the automated and systematic improvement of the O&M strategies and assets management of an offshore energy farm, as proposed at the beginning of this thesis, a number of guidelines and research needs can be identified.

As discussed in Section 5.2, a generic mixed methods approach uses, at each iteration, an optimisation model to propose the set of inputs that are evaluated with the simulation model, as illustrated in Figure 5.1.

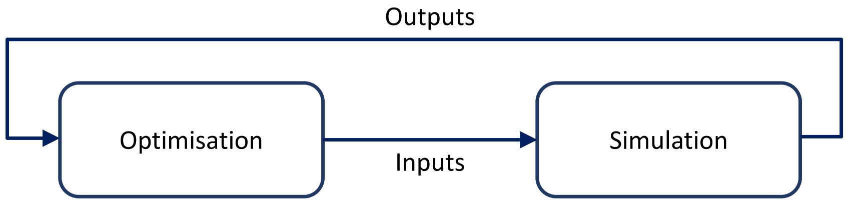

Figure 5.1: Schematic representation of a mixed simulation and optimisation approach. Adapted from Glover *et al.* (1996).

Within the aims of this work, the ideal framework would embody the models presented in such a way to exploit both the accurate prediction of the KPIs with the characterisation model and an automated progression towards improved solutions with the optimisation algorithm. However this is not feasible at the present stage due to the computational limitations of the characterisation tool and the lack of a proper link between the two models. As a consequence, future work will consist in decreasing the simulation time of the Monte Carlo tool by analysing the code in order to find bottlenecks in the simulation, using parallel computing and seeking less computationally demanding (but able to deliver the same result) functions. At the same time linking functions will be implemented in order to have the characterisation tool evaluate every individual (solution) proposed within the optimisation search procedure. This will allow for the final coupling between Monte Carlo and GA methodologies, achieving the automated optimization of the O&M assets based on the accurate estimations of KPIs. This concept is illustrated in the flowchart in Figure 5.2, which resumes the concept illustrated at the beginning of this work in Figure 1.2 and adapts it to the coupled tools.

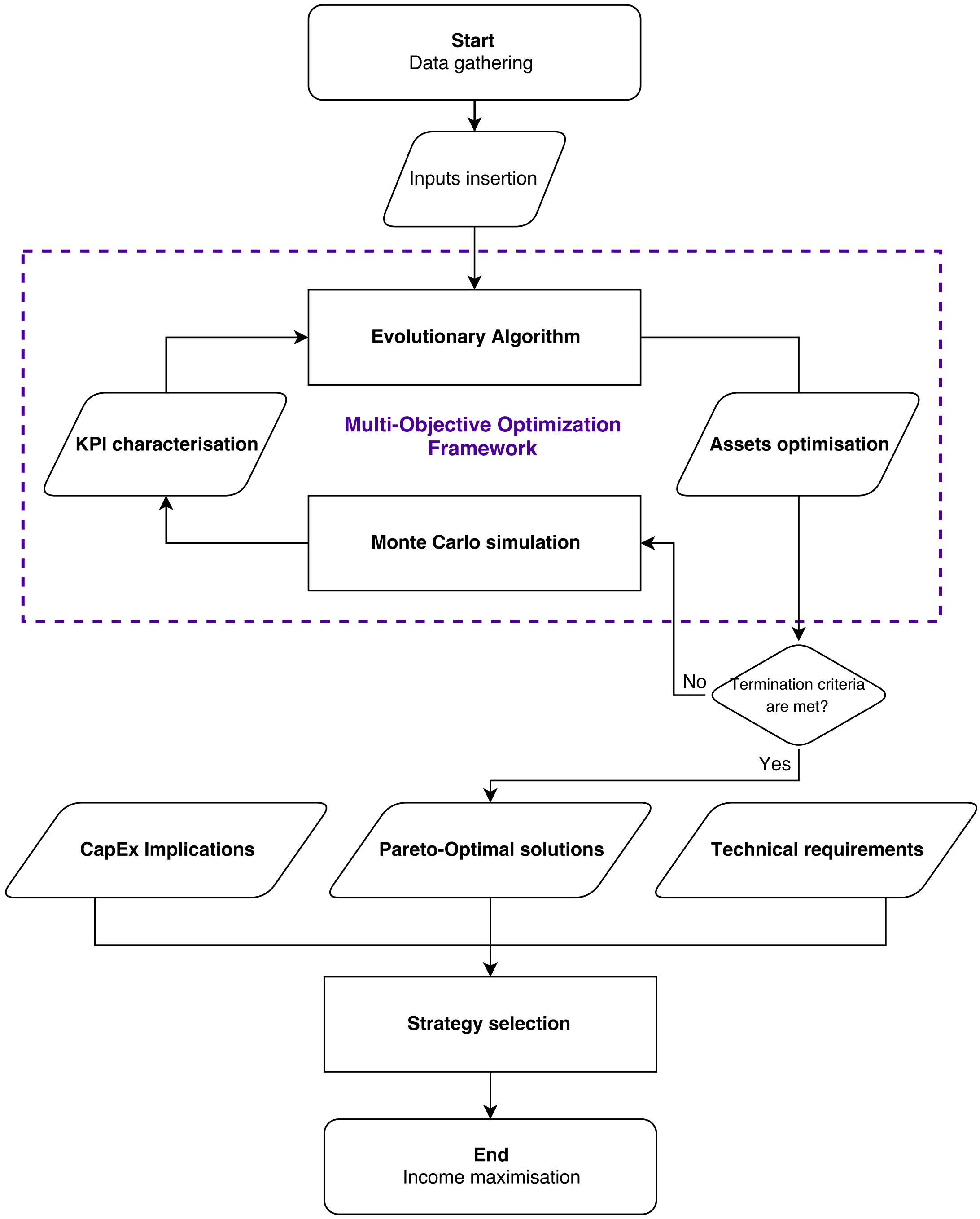

Figure 5.2: Flowchart of the future methodology including both models in a single characterisation and optimisation framework.

Chapter 6

Conclusions and future work

Contents

Offshore renewable devices hold a large potential to become important energy generation systems, and O&M activities together with clever assets management will be key areas to increase their viability and competitiveness. However, in order to decrease costs and improve the availability of the devices, advanced methodologies and simulation tools will be required to support the decision-making process.

At the beginning of this thesis an overarching research question was set out: *How can operation and maintenance procedures for offshore renewable energy farms be improved in an automated and systematic way?*

Following this overarching question, three subsequent key research questions were set out in order to address it; these were:

1. Is there an effective way of modelling the dynamics of an offshore energy farm in order to accurately estimate its key performance indicators?

2. Given the information of the offshore farm and its productivity estimations, can the best logistics and maintenance assets be established in an ingenious and reliable way not necessarily subject to the experience and judgement of a decision-maker?

3. What would be the potential implications of such tools and methodologies on the offshore farm maintainability and profitability?

The discussion sections, both at the end of each case study in Chapter 4 and in the summary discussion in Chapter 5, outline how these research questions have been addressed through the work presented in this thesis. In particular, the implementation of the Monte Carlo characterisation tool and described in Section 3.1 affirmatively answers to the question 1, the implementation of the optimisation tool based on GAs and described in Section 3.2 affirmatively answers to the question 2, and the case studies discussed in Chapter 4 show the potential implications of these methodologies on the offshore farm maintainability and profitability, both in terms of accurate characterisation of the key performance indicators and comprehensive optimisation of the assets management.

As a consequence, this thesis details a combination of computational tools that can be used to obtain a detailed overview of the distinctive features of an ORE farm, and support the decision-making process in order to create the optimal environment for its management and operation.

This chapter will be used in order to summarise the main achievements and conclusions from the present work, as well as to detail recommendations for future work.

6.1 Summary

The review of requirements and characteristics of the different maintenance strategies, as well as the already existing computational models for the O&M of offshore renewables, in Chapter 2 led to the choice of a Monte Carlo stochastic modelling for the characterisation of a farm KPIs. Apart from the high prevalence of this methodology in other works, this choice was made by taking into account the ability of capturing the stochastic nature of failures, the suitability to use discrete event modelling for the maintenance operations and practical considerations regarding the computational implementation. However, this is not the only methodology available to properly interpret both corrective and planned maintenance interventions or provide support in the decision-making process. It is worth noting that generally these models are mainly concerned with the correct interpretation of the input data provided. Nonetheless, a strong dependence on reliability and other data, for which there is often uncertainty and commercial sensitivity, exists. For this reason, reliability data for offshore renewable technologies and assessment techniques are briefly included in the conceptual framework.

Within Chapter 2, the problem of reaching the ideal trade-off when competing objectives are considered is described, and suitable techniques used in renewable energy related problems reviewed. Also in this case, though evolutionary algorithms are found to be the most used in this area, other suitable approaches exist. Nonetheless, genetic algorithms are selected due to their adaptability to different problems, ease of control and implementation, and effectiveness in finding optimised solutions, and their working principle is described. Finally, optimisation models for offshore renewables are reviewed, and the gap in a specific optimisation framework for the O&M strategic planning support identified.

In Chapter 3 the methodology implemented to create the overall optimisation framework is outlined, with respect to the two individual models: the Monte Carlo characterisation model and the GA based optimisation model. A schematic description of both models is provided and an illustrative example of their application, with direct repercussions and implications of the findings, is given in the following Chapter 4. Here the insights that the methodologies provide are presented. In the first case study, Section 4.1, the repercussions of choosing a more capable maintenance system between two available are shown, and the performance indicators that the model provides, together with how to use them to analyse the effectiveness of a solution, are illustrated. In the second case study, Section 4.2, the procedures used to gain confidence in the implemented models, as well as guidelines for the benchmarking with a surrogate model, are described. In the third case study, Section 4.3, the insights provided by the optimisation framework by obtaining the ideal value for each of the decision variables in the problem of managing the assets of an ORE farm, in a simple and automated way that leaves aside the hassles of manually testing several alternatives, are presented. In addition, an idea of the economical benefits that an optimisation of the maintenance assets can deliver is provided.

The brief discussions at the end of these sections analyse the results obtained for each case study, highlight the capabilities of the models, and provide an opportunity to identify the future areas of improvement described in the following section.

Finally, Chapter 5 extends the discussion on both the approach and results of these modelling works. Here, the advantages of an automated optimisation based on the use of genetic algorithm, as opposed to a subjective proposal of alternative strategies, is highlighted. Similarly, advantages and limitations of a verification process, as opposed to validation against a real scenario, are discussed, concluding that a validation of such methodologies is rather impractical and, assuming it was plausible, would not assure the complete reliability of the tool. The use of all the three GA approaches proposed in this work is advised for any case study in order to obtain a more comprehensive panorama of the possible solutions and O&M strategies. The reliance on the human element in the decision-making is highlighted, although the risk of missing possible improvements or proposing ineffective solutions is reduced. The need of introducing CAPEX elements in the characterisation tool for a fair verification of the proposed solutions is pointed out.

To conclude, this chapter identifies a series of key features and suggested work in order to improve the current state of decision making tools for offshore renewables.

6.2 Further thoughts

The content of this thesis is mainly based on the development of two individual models, thus proposals for further work are provided for each of these individually.

6.2.1 Characterisation model

Following the literature review in Chapter 2 and the implementation of the characterisation model according to best practices and academic standards, a series of considerations for future improvements can be identified.

Additional features will allow for the creation of a more effective tool, which taking into accounts a higher number of aspects related to the operational lifetime of an offshore renewable farm, will satisfy industry requirements to a larger extent and will meet the requirements for future, bigger, ORE farms. In introducing these additional features, the approach chosen so far of trying to provide as many modelling possibilities as possible but without overextending the number of minimal information in order to run the model, will be preserved. In other words, a more flexible tool, able to grasp more aspects of the operation of the ORE farm and deliver an improved decision-making experience will be achieved.

Examples of these features may include, but are not limited to: ownership of part of the maintenance fleet, optimal routing among devices, grouped maintenance activities, probabilistic modelling of more input parameters (e.g. repair and procurement time), extension of the statistical indicators, sea-based maintenance system and multi-device ORE farms.

Despite having been implemented in a series of works (e.g. Dinwoodie (2014) and Gray *et al.* (2017)), the forecast of MetOcean time series is not among the immediate objectives for future work. This modelling work would add an additional level of stochasticity to the problem, allowing for the analysis of a larger number of different scenarios and providing an additional method to quantify accessibility related risks. However, assuring the correct persistence properties could be challenging. As a consequence, analogously to what had been discussed for the simulation of fault detections by means of condition monitoring, after discussion with the industrial partner of this project and according to previous projects (Mermaid), it has been decided that it would also add a further level of uncertainty on the results obtained, and therefore it has not been prioritised among the immediate improvements of the model.

Nonetheless, as discussed for the reliability input data, also for the time series the model is mainly concerned at correctly interpreting the information, provided that its truthfulness is first guaranteed by other means. Thus, nothing prohibits the use of synthetic MetOcean data instead of hindcast data with the characterisation tool.

Regarding the condition monitoring, similar considerations may apply, therefore rather than a dedicated CM model, the characterisation tool should be equipped with a method to include and interpret CM logs (if available) or considerations of the ORE farm under investigation.

6.2.2 Optimisation model

Similar to the characterisation tool, according to the identified trends in literature, the considered requirements and the implementation of the optimisation model, a series of future improvements has been identified also for the optimisation framework. However, these improvements do not aim at extending the number of features available within the model, but aim instead at a refinement of the search procedure for optimal solutions.

For example, additional work will be needed in order to find suitable rules or indications to systematically tune the parameters that regulate the algorithm. In this regard, hypotheses for self adaptation of the control parameters will also be considered by implementing a feedback mechanism on the quality of the solutions found during the search (e.g. by quantifying how much the average solution is far from an ideal pre-established value).

Another improvement consists in further refining the objective functions by both reconsidering their formulation after the implementation of the new features proposed above for the characterisation tool, and further benchmarking them using different case studies and variations. Furthermore, a vast number of GAs approaches exist and shall be compared to verify if better solutions can be found by using other variants. Despite this has been partly done through the implementation of the three approaches implemented and compared in this work, more approaches can be tested.

On the other hand, despite having selected genetic algorithms as the best suited methodology in order to represent this problem, other suitable techniques mentioned in previous Chapter 2 (e.g. neural networks and particle swarm optimisation) shall be explored and compared in terms of quality of the results obtained and computational performance. In addition, other approaches based on both nature-inspired and not optimisation methods could be tested for more cases, in order to assess the best methodology for each case or type of problem and provide a range of indications in order to choose, case by case, the most suitable approach.

To summarise, improvements in the optimisation model may be obtained by:

1. Modifying evaluation functions and control parameter using the same GA approaches;
2. Exploring the use of different GA approaches; and
3. Exploring the use of different optimisation methodologies.

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Appendix A

Multivariate analysis of the reliability, availability and maintainability characterisations of a Spar-Buoy wave energy converters farm

The case study presented in this section is used to show the applicability of the characterisation model to wave energy converters and demonstrate the multivariate analysis as a valuable alternative to the sensitivity analysis. It considers a pilot wave energy converter farm of 10 floating oscillating water columns (OWCs) to be deployed off the coast of Portugal. For a complete description of the input data used for this study the reader can refer to paper number 7, Rinaldi *et al.* (2018c), provided in the List of Publications at the beginning of this thesis.

Under these premises, the values for the different output variable obtained by averaging the results over the total number of simulations (100) are reported in Table A.1. However, in order to add statistical relevance to the research, check the properties of the output variables and establish a correlation between their mutual influences with the aim of gaining insights on the properties of the farm, the results generated during each run of the simulation are analysed. Firstly, the cumulative probabilities of the most relevant performance indicators, together with their exceedance probabilities

Table A.1: Performance indicators for the 1.5MW wave energy farm case study.

Quantity	Value
Average annual energy (MWh)	2261
Average annual loss (MWh)	12
Capacity factor (%)	17.29
Equivalent hours	1515
Availability (%)	99.48
Total gross production over 10 years (m€)	5.88
Total lost production over 10 years (m€)	0.03
Total O&M costs - Repairs, vessels and crew (m€)	3.60
Total generated income over 10 years (m€)	2.28

P10, P50 and P90, are plotted together (Figure A.1). The selected indicators are: energy delivered over the lifetime, total gross revenue, availability, income after O&M costs, cost of repairs and replacements, total number of simulated failures for the whole offshore farm.

These variations can be visualized also by means of box plots, as illustrated in Figure A.2. On each box, the central red line indicates the median, while the bottom and top edges of the box indicate the 25^{th} and 75^{th} percentiles respectively and the red '+' symbol indicates the outliers.

Therefore, the selected KPIs are plotted against each other two at a time, with the respective histograms along the diagonal in Figure A.3.

At this point the PCA is used on these sets of data to plot all the results of the iterations simultaneously, as illustrated in Figure A.4. Here, all the selected variables (energy, revenue, income, availability, cost of repairs and number of failures) are represented by a vector, whose length and direction indicate the contribution of each variable to the two principal components in the plot. Thus, the first principal component (i.e. the horizontal axis) mainly distinguishes between solutions having high (on the right) or low (on the left) repair cost and number of failures, as well as low (on the right) and high (on the left) availability, energy production and gross revenue. Instead, the second principal component (i.e. the vertical axis) can be used to distinguish solutions having high (below x-axis) and low (above x-axis) incomes, as well as high (above x-axis) and low (below x-axis) availability, energy production and gross revenue. Only the first two principal components are selected because, after analysing the percent variability

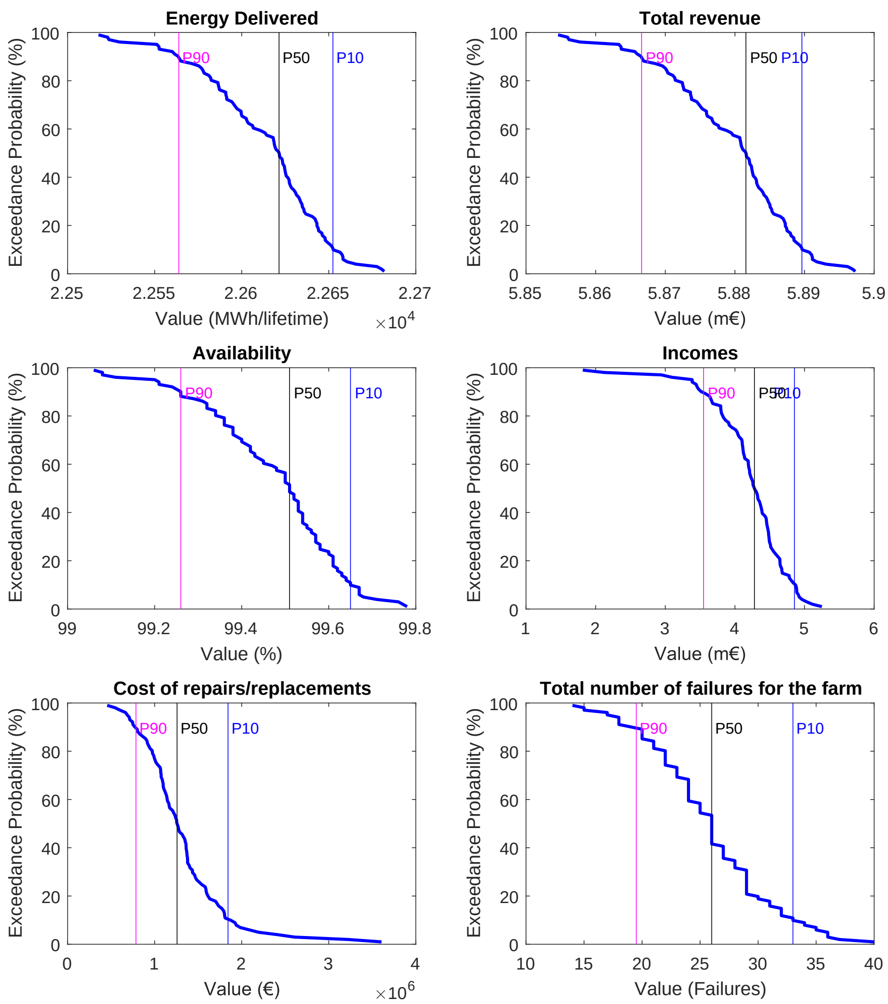

Figure A.1: Cumulative probabilities of the most relevant KPIs over the simulations.

explained by each principal component, these contain 93% of the total variance (68% for the first component and 25% for the second respectively). In this figure, each of the 100 observations produced during the simulation is represented by a red dot, whose coordinates indicate the score of each observation with respect to the two principal components. The utmost points of the plot represent the most significant variations in terms of one or more of the original output variables, hence are selected for their relevance and labelled by their number. Therefore, these observations are investigated in terms of the original KPIs, and the values shown in Table A.2 are obtained. These

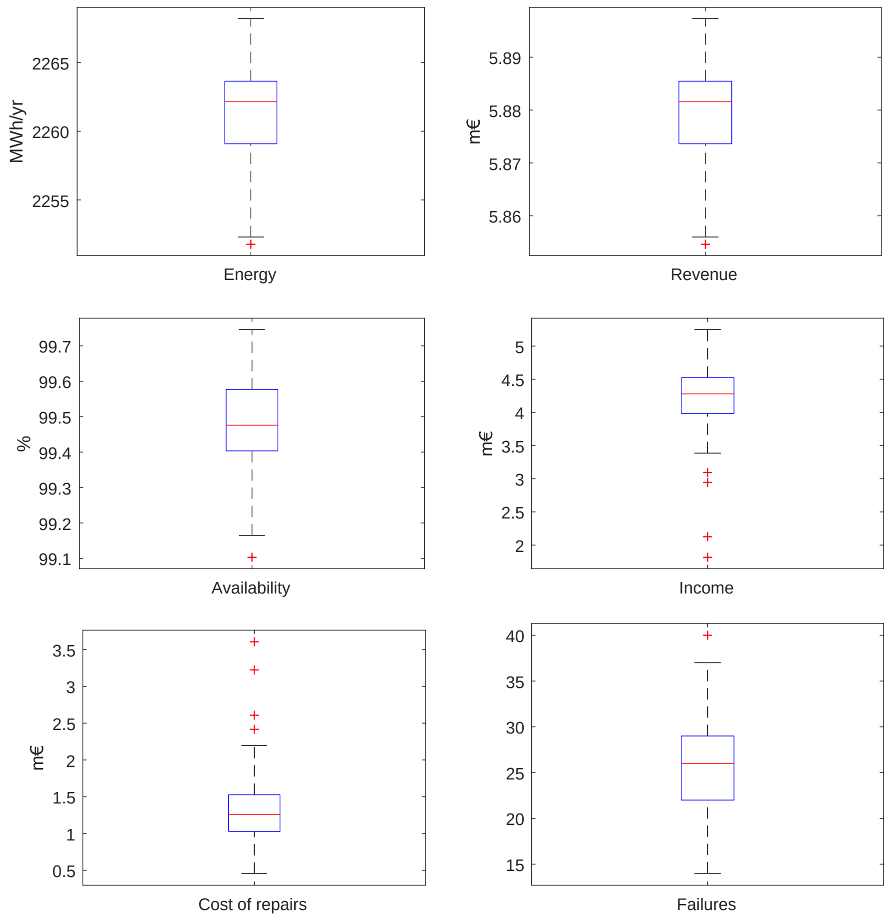

Figure A.2: Box plots of the most relevant KPIs over the simulations.

and the other results of the analysis will be discussed in the following section.

When looking at the KPIs averaged over all the iterations of the Monte Carlo simulation, the following considerations can be made. Firstly, the value of energy produced is very close to that obtainable in the ideal case of absence of corrective maintenance interventions; analogously, the average availability is close to 100%. This can be explained due to two main reasons. The first one, as already mentioned, is the exploitation of the great difference in the capabilities of the access systems. This permits to use the cheaper and faster CTV for most of the maintenance (around 97% of the interventions) switching to the Multicat only when major maintenance actions are needed.

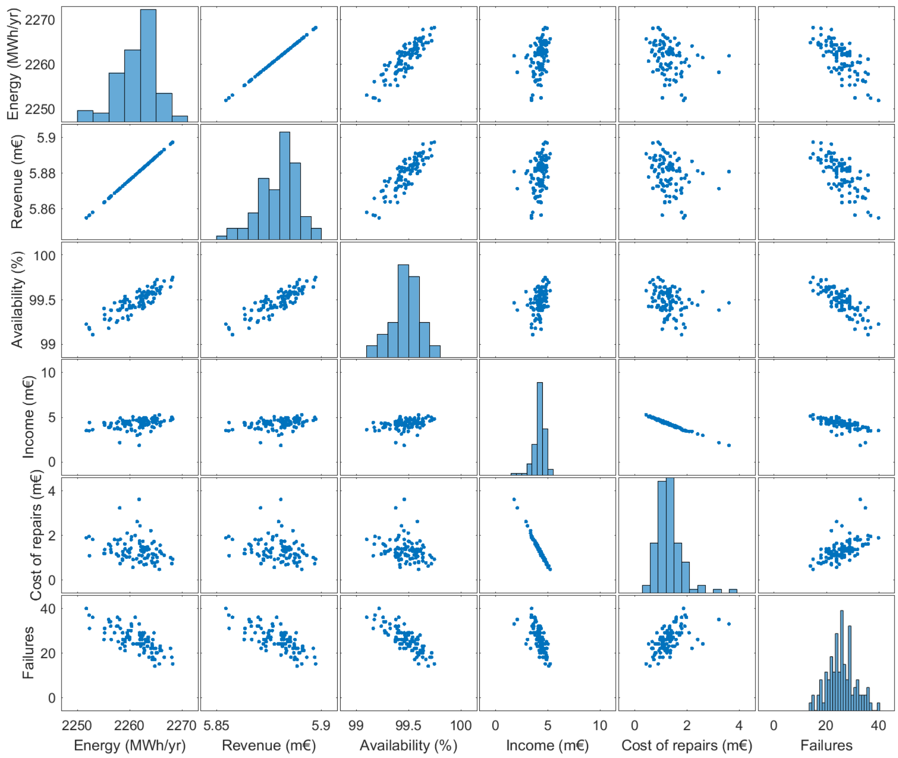

Figure A.3: Scatter plot and histogram matrix of the most relevant KPIs over the simulations.

This, in turn, allows for quicker repairs and replacements that reduce the inactivity of the devices and avoid the risk of persistent downtimes due to the lack of proper maintenance systems available. The second reason is the choice of the offshore farm site. This is not only close to the coast, but also to the harbour for the maintenance operations (Figueira da Foz' Port), making all procedures shorter and more efficient. In addition, the wave climate is relatively mild, allowing for high weather windows availability (therefore accessibility of the offshore farm) for most of the times a maintenance operation is needed. The capacity factor, despite its low value, is a relative measure and it is strongly sensitive to the rated power selection, which in turns has important implications on the annual energy produced. Analogous considerations can be made for the equivalent hours. Regarding the economic indicators, as mentioned in the previous section these have been estimated according to the feed-in-tariff for demonstration

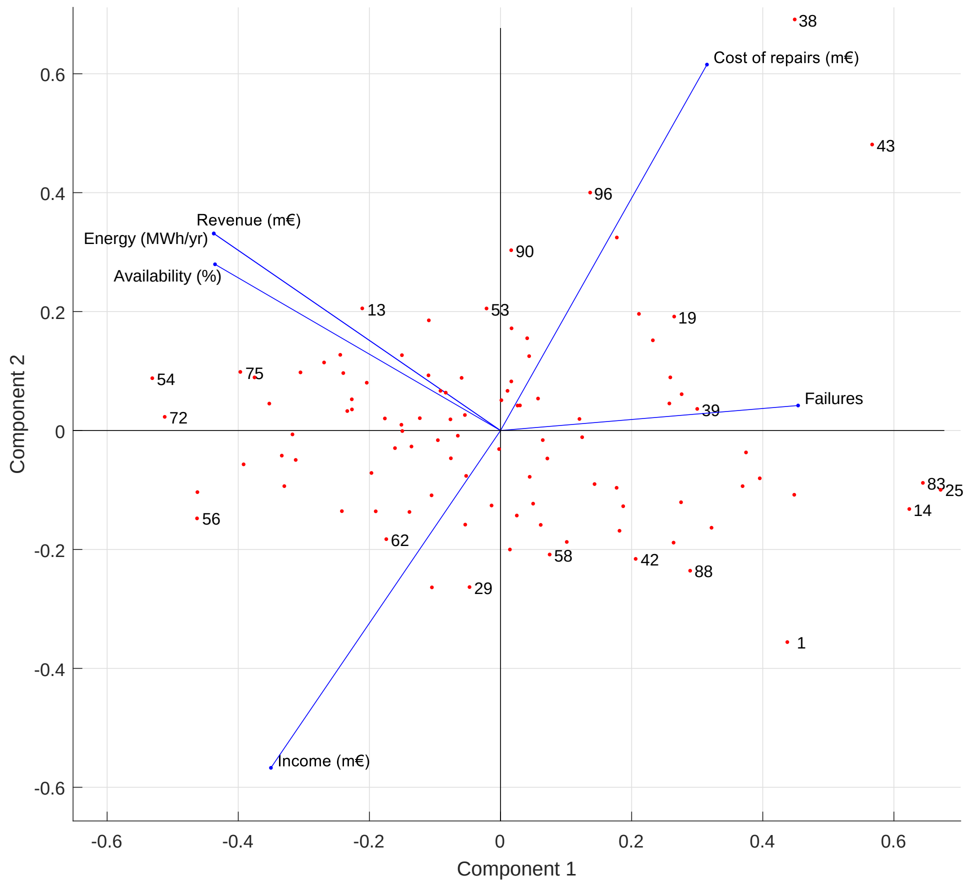

Figure A.4: Results of the PCA on the original results of the Monte Carlo simulation. The principal components are represented by the axis, the analysed output variables by the blue vectors and the results with respect to these variables for each of the 100 simulations by the red dots.

projects. Although, for this case they are positive reaching €2.28m of generated income over the simulated lifetime (10 years), it is noted that current electricity market prices might be lower than those offered in the feed-in-tariff mechanisms, and care should be taken when assessing economically the O&M costs versus the revenues and profits.

When the statistical distributions are analysed, different ranges of variations are observed for the selected KPIs. Looking at the chart for the observed variables plot two at a time in Figure A.3, it is possible to notice a certain linearity between two sets of variables: energy production with revenue (but this is intuitive because the revenue

Table A.2: Performance indicators for the selected iterations (utmost solution in Figure A.4) of the Monte Carlo simulation selected after PCA.

Case	Iteration	Availability (%)	Energy (MWh)	Revenue (m€)	Income (m€)	Repair cost (m€)	Number of failures
1	38	99.46	2261.80	5.88	1.81	3.60	33
2	43	99.37	2258.10	5.87	2.12	3.22	35
3	96	99.58	2261.40	5.87	2.94	2.60	24
4	19	99.40	2261.10	5.87	3.44	1.98	36
5	39	99.38	2257.80	5.87	3.68	1.77	32
6	83	99.18	2252.30	5.85	3.45	1.93	37
7	25	99.22	2251.79	5.85	3.47	1.87	40
8	14	99.10	2253.00	5.85	3.58	1.80	36
9	1	99.16	2252.40	5.85	4.38	1.06	31
10	88	99.27	2255.19	5.86	4.32	1.16	29
11	42	99.39	2255.10	5.86	4.37	1.16	26
12	58	99.40	2258.70	5.87	4.64	0.86	29
13	29	99.47	2258.19	5.87	4.88	0.71	22
14	62	99.41	2262.70	5.88	4.92	0.66	22
15	56	99.59	2265.69	5.89	5.24	0.45	15
16	72	99.71	2268.00	5.89	4.96	0.70	18
17	54	99.74	2268.20	5.89	4.77	0.91	15
18	75	99.70	2266.60	5.89	4.55	1.09	18
19	13	99.63	2265.80	5.89	4.04	1.54	23
20	53	99.51	2264.60	5.88	3.80	1.70	29
21	90	99.45	2264.00	5.88	3.38	2.19	22

is calculated proportionally to the energy produced and the electricity strike price) and the cost of repairs with the incomes. Less marked linearities can be seen between revenue and income, and failures and income. This can be better observed when only the economic quantities are selected and visualised in the same boxplot using the same scale on the y-axis, as shown in Figure A.5. Income and cost of repairs distributions are wider than the revenue distribution; therefore there is not much variability along the simulation for the energy production (then the revenue), while there is more variation for the cost of repairs/replacements (then income). This gives further proof of a significant relationship between repairs cost and generated income. However, from the results shown in Figure 13, while the linear dependence between cost of repairs and generated income is evident, it is not possible to clearly identify a similar dependency for energy, revenue and availability. This is because the non-linearity of some correlations could make the interdependencies harder to be noticed in a simple 2D scatter plot. Hence, this supports the hypothesis that alternative techniques, such as the multivariate analysis using PCA, are needed in order to gain a deeper level of understanding on the mutual dependencies among variables.

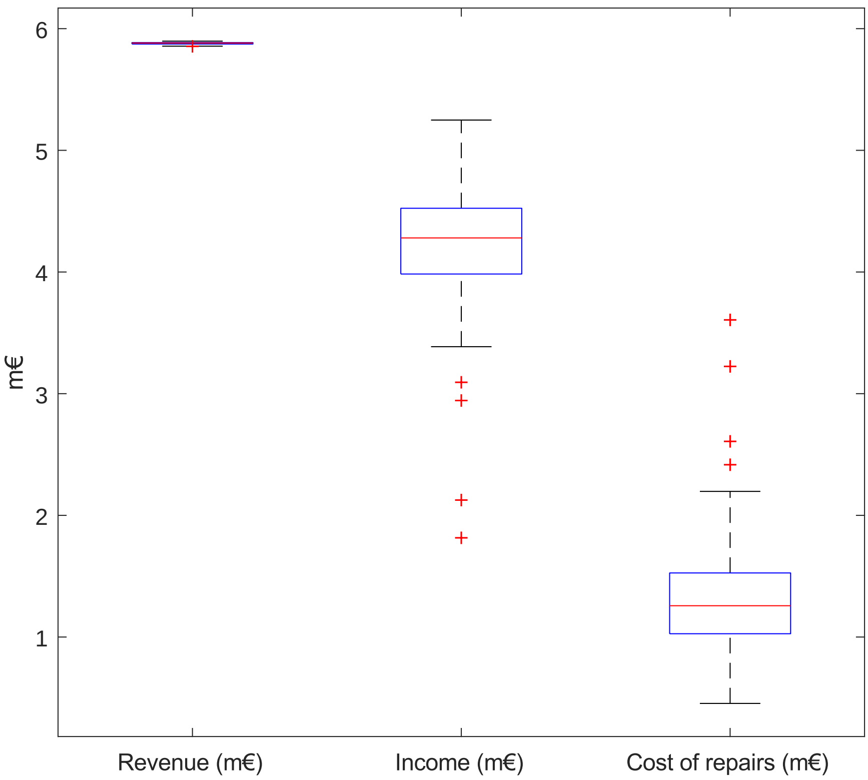

Figure A.5: Scatter plot and histogram matrix of the most relevant KPIs over the simulations.

Finally, thanks to the indications of the PCA from Figure A.4, the values in Table A.2 for the utmost selected solutions are obtained. In this table, the first column simply indicates the order in which the results of each iteration of the simulation are considered, the second column indicates the corresponding iteration over the total 100 produced during the Monte Carlo simulation (these correspond to the utmost solution labelled by a number in Figure A.4), and all the successive columns represent the values of the original output variables for the related case. Thus, by examining the values in Table A.2, the following observations can be made:

- The best income (case 15) is obtained not in correspondence of the maximum energetic production or availability (case 17), but for the minimum repair cost (case 15);
- Cases 15 and 17 have the same number of failures (15), but the repair costs of case 17 are twice those of case 15;
- Although case 7 has the highest number of failures (40) and case 3 many less (24), the repair cost for case 3 (2.6m€) are much higher than for case 7 (1.8 m€);
- Energy production and gross revenue are proportional to one another for all the cases (due to the way the gross revenue is calculated); however the availability is not necessarily proportional to these because of the differences in wave resource distribution over time (if a device enters in downtime when the wave resource is scarce or null, the energy production will not be affected).

As a consequence, the cases that provide the most significant singularities (cases 3, 7, 15, 17) are further analyzed and the following outcomes emerged:

- Case 3 is the only one in which a failure of the buoy structure is simulated (this is by far the most expensive failure, 1.3m€);
- The high number of failures in case 7 are due mostly to moorings (17) and the electric generator (10). In this regard, the failure rate of the electric generator is much higher than that of the buoy structure. However 10 failures of the electric generator are still cheaper to repair than 1 of the buoy structure, which explains the difference in replacement cost with case 3;
- Repair costs of case 15 are lower than those of other cases because most of the failures are due to the moorings, that are cheap to repair compared to other components;
- In case 17 there are failures of components having relatively low failure rate (like turbine, sensors and PTO control system). Even if these are a limited number (1 to 3) this significantly increases the cost of repairs.

From these analysis, generic conclusions that could have not been drawn by only looking at the results averaged over all the simulations, are:

- The cost of repairs is a major driver of the O&M costs;
- The reliability of the components, especially due to the cost of eventual repair actions, is pivotal for the profitability of a project;
- Solutions that maximize the energy production or the availability of the farm may not be the most cost effective if the other cost drivers are neglected or secondary importance is given to these;
- The failures of few components might make the difference between a successful and an unsuccessful project;
- The effects of a failure (caused downtime and, especially, repair cost) are more relevant than the frequency of a failure (failure rate) for the purpose of profitability. Thus, if a choice is available, it may be better to use components with higher failure rate but that are cheaper to repair or replace than components that are more reliable but more expensive to repair;
- The choice of using less reliable components may be mitigated by more frequent maintenance interventions when the resource is smaller and the production is not affected, especially if eventual maintenance interventions are facilitated by proximity to the O&M port.

To summarise, the use of a verified computational tool allows for the accurate estimation of the key performance indicators of an offshore energy farm, while the multivariate analysis permits the identification of previously unidentified interdependencies and correlations. In this way, more effective improvements on the viability of the project, calibrated to the specific offshore farm considered, can be obtained in an efficient way and with reduced cost and effort.

Appendix B

Input sheets example

An example of the input sheets used to include the properties of components and vessels in the characterisation model is shown in Figures B.1 and B.2. All these entries have been fully presented and discussed in Section 3.1.1, but are briefly described here for clarity.

System or single component.	Comp. 1	Comp. 2	Comp. 3	Comp. 4	Comp. 5	Comp. 6	Comp. 7	Comp. 8	Comp. 9
Subsystem	1	1	1	1	1	1	1	1	1
Procurement time	0	0	0	0	0	0	0	0	0
Repair time	89	67	31.25	22	20.75	17.5	17.5	13.25	12.75
Annual Failure rate	0.538	0.4995	0.52	0.2355	0.2175	0.215	0.214	0.392	0.173
Environmental factor	1	1	1	1	1	1	1	1	1
Failure rate in Failures\Hour	6.14155E-05	5.70205E-05	5.93607E-05	2.68836E-05	2.48288E-05	2.45434E-05	2.44292E-05	4.47489E-05	1.97489E-05
Repairable/Replaceable Overnight (Y = 1, N = 0)	1	2	0	0	1	0	0	1	0
A (scale parameter) - Early									
B (shape parameter) - Early									
A (scale parameter) - Constant									
B (shape parameter) - Constant									
A (scale parameter) - Aging									
B (shape parameter) - Aging									
Maintenance category	2	2	3	1	2	2	2	1	1
Fault type category	4	4	2	10	7	7	7	9	9
Criticality for the subsystem (Y = 1, N = 0)	1	1	1	1	1	1	1	1	1
Redundant Components	0	0	0	1	1	1	0	0	1
k-out-of-N necessary comp.	0	0	0	1	1	1	0	0	1
Cost Replacement (£)	65910	25973	18037	5253	4550	4564.5	4431	4306	3995
Spare Parts in stock	0	0	100	100	0	100	100	0	0
Number component	1	2	3	4	5	6	7	8	9
Common Cause Failures (Y = 1, N = 0)	0	0	0	0	0	0	0	0	0
Relying on component	0	0	0	2	0	0	0	1	0
Direct fail (Y = 1, N = 0)	1	1	0	0	1	0	1	1	0
Failure Rate variation (%)	50	-30	0	0	20	35	0	12	0
Additional crew members	1	0	0	-1	0	0	0	0	1

Figure B.1: Component inputs sheet (example).

- **Subsystem**. This is the identification number assigned to each of the different subsystems in the device. Every component belonging to the same subsystem should have the same subsystem number. The number of the subsystem must be sequential, from 1 to N (total number of subsystems).

- **Procurement time**. Indicates the required time (in hours) to find a spare part for the selected component. If set to 0 (zero) it means that it is stock in site, then immediately available.

- **Repair time**. Indicates the required time (in hours) to execute the repair or replacement for the selected component.

- **Annual Failure rate**. Number of failures per year for the selected component.

- **Environmental adjustment factor**. This factor takes into account the increase in failure rate due to harsher environmental conditions that have not been considered during the failure rate collection. Please remember that these adjustments are dependent on the database used, the kind of component and the ground environment they refer to. Base value set to 1. Some values suggested by Davidson (1994) are 2 for exposed components, 1.5 for sheltered components.

- **Failure rate**. Failures per hour. It is calculated from the annual failure rate dividing that value by 8760 (number of hours in a year) and multiplying it by the environmental factor.

- **Repairability/Replaiceability Overnight (Y = 1, N = 0)**. Establishes if the component is repairable or replaceable during the night. If also the selected vessel has this property then the operation will be executed at any time, otherwise daylight has to be awaited.

- **Weibull distributions parameters**. To be inserted only if this information is available. Two parameters are required, respectively scale parameter A and shape parameter B, to be put on the first two lines (Early). If available, six parameters can be used for each of the three phases of bathtub shaped failure rate (early mortality, constant failures, wear out).

- **Maintenance category**. Establishes the maintenance category for the selected component, as described in Section 3.1.1.
- **Fault type category**. Establishes the fault type category for the selected component, as described in Section 3.1.1.
- **Criticality for the subsystem (Y = 1, N = 0)**. Establishes if the component is critical or not (needed for its functioning) for the subsystem to which it belongs.
- **Redundant Components**. Establishes the number of redundant elements added to the component indicated. Number of additional components, i.e. if this value is equal to 2 it means that there is a total of 3 identical redundant components.
- **k-out-of-N necessary comp**. Indicates how many of the total redundant components are necessary for the functioning of the subsystem to which they belong. This number cannot be higher than the number of redundant components + 1. For instance, if redundant components is equal to 3 it means that there is a total of 4 identical redundant components of that kind; if k-out-of-N is set to 2 it means that at least 2 out of 4 redundant components have to be functional at the same time to leave the subsystem functioning.
- **Cost Replacement**. Is the cost associated to the repair or replacement of the component. It includes cost of the spare part and labour. This is taken into account in the final evaluation of the maintenance costs.
- **Spare parts in stock**. Indicates the number of available spare parts in stock at the beginning of the simulation. When a failure happens the number of spare parts available dicreases by 1. Every repair/replacement is executed only if there is always a number of spare parts available higher than 1.
- **Number component**. It is just an identifying number to be associated with each component in order to facilitate the process of assigning dependencies between components.
- **Common Cause Failures (Y = 1, N = 0)**. Establishes if the component is subject to common cause failures with other components. In other words, it indicates if the component can fail or endure a variation of its failure rate as a

consequence of another component's failure. N.B. These rules are followed only if there is compatibility with rules on criticality, which have the priority (e.g. a direct fail cannot happen simultaneously on 2 critical components because the device is already in downtime in that case).

- **Relying on component**. Indicates in which other components failure the selected component relies for common cause failures.

- **Direct fail (Y = 1, N = 0)**. Indicates if the effect of the other component's failure is a failure as well (cascading failure).

- **Failure Rate variation (%)**. Indicates the variation in percentage of the failure rate due to the failure of the other component on which it depends. This can be positive (positive dependency) or negative (negative dependency). Should be used only if Direct fail = 0.

- **Additional crew members**. Indicates the number of additional crew members needed for the maintenance of the components with respect to those indicated in the corresponding fault category. This can be positive (more members) or negative (less members).

Name of the vessel	Vessel 1	Vessel 2	Vessel 3
Identification number of the vessel	**1**	**2**	**3**
Response time	1.35	2.25	2.45
Overnight Operations	0	0	1
Vessel Maintenance Category	1	2	3
Fleet	4	7	5
Day rate (£)	1750	9500	150000
Standby rate (£)	0	0	0
Mobilisation cost (£)	0	0	27000
Transit fuel cost (£)	138	883	2187
Average daily crew member cost (£)	220	220	220
Seasonality	0	0	0
Seasonality - Start month	1	1	1
Seasonality - End month	12	12	12

Figure B.2: Vessels inputs sheet (example).

- **Identification number of the vessel**. Number of the vessel; to each number corresponds a different vessel.
- **Response time**. Vessel response time in hours. It includes the time to prepare and assemble maintenance crew and equipment (preparation) and reach the farm from the selected port (mobilisation). This value should be variable with time, depending on MetOcean conditions (output from Mermaid).
- **Overnight Operations**. Able to operate during the night (Y = 1, N = 0).
- **Vessel Maintenance Category**. Vessel Maintenance Category (see Section 3.1.1 for more information).
- **Fleet**. Number of vessels of that kind available in the fleet (rented or purchased).
- **Day rate**. Daily rate of the vessel; considered only for those days when the vessel is used (the vessel is in any state other than in port, fee incurred per working day). If the vessel is a property of the farm this may be set to 0.

- **Standby rate**. Fee incurred per non-working day. This should include the daily port fees (mooring and port expenses) in case the vessel is property of the farm. It may be set to 0 if the vessel is rented only when needed for maintenance (moorings and port fees would be included in the daily rate in this case).

- **Mobilisation Cost**. Cost for the mobilisation of the vessel due to a corrective or planned maintenance operation; this is considered only for those times that the vessel is actually used because required for offshore operation. Fee incurred per port departure.

- **Transit fuel cost (£)**. It is the cost of the fuel needed for one single transit from the O&M port to the offshore location. This can be obtained by Mermaid or calculated alternatively.

- **Average daily crew member cost (£)**. Average price for each crew member for each day of intervention. This will be multiplied my the number of members in the crew established in the component table. If the vessel crew costs are included in the vessels rates put 0.

- **Seasonality**. Indicates if the vessel is chartered only for one or more specific months (e.g. summer) = 1 or not (i.e. available all year round) = 0.

- **Seasonality - Start month**. Number of the month (1 - 12) when the restricted availability of the vessel begins.

- **Seasonality - End month**. Number of the month (1 - 12) when the restricted availability of the vessel ends.